IDENTIFYING VARIATIONS OF SOCIO-SPATIAL VULNERABILITY TO HEAT-RELATED MORTALITY DURING THE 1995 EXTREME HEAT EVENT IN CHICAGO, IL, USA

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ABSTRACT

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Extreme Heat Events are the leading cause of weather-related mortalities in the continental United States. Recent publications have suggested that vulnerability to extreme heat is impacted by variations in environmental and socioeconomic conditions, even across small spatial units. This study evaluated the usefulness of socioeconomic variables and satellite-derived environmental measurements as predictors of heat-related vulnerability during the July 14-17, 1995 heat wave in Chicago, IL. Geospatial analysis and statistical processes were implemented to identify and rank characteristics of vulnerable populations. Results suggest population density, educational attainment, age, and financial indicators are among the best predictors of heat vulnerability. Proximity to and intensity of Urban Heat Islands also appears to influence neighborhood vulnerability levels. Identification and mapping of vulnerability variables can distinguish locations of increased vulnerability during extreme weather conditions. These vulnerability maps could be utilized by city officials to plan and implement aid programs to specific high risk neighborhoods before an extreme heat event, and resulting health implications, occur. Continued study and implementation of these variables could also assist in identifying vulnerable populations in other urban environments, improve utilization of

location-specific heat warning systems and impact new building policies to decrease vulnerability variables across the country.

Daniel P. Johnson, Ph.D., Chair

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INTRODUCTION

Heat is one of the most preventable causes of mortality in the United States. It continues, however, to be the leading cause of weather-related death (Dolney and Sheridan 2006, Robinson 2001, Davis 1997). Heat is deadly because it exacerbates pre-existing health conditions, and offers little visible warning of inclement weather without the use of meteorological instruments or public announcements. Other deadly weather events, such as blizzards or tornados, are preceded by clouds and a drastic change in weather conditions. Heat waves, on the other hand, stealthily move into an area, providing little visible warning before the population's health has been affected. Heat also typically experiences less media attention, because most disaster aftermath is quantified through monetary assessments. Heat does not physically damage structures, so many media and insurance companies do not know how to quantify the impact a heat wave has on an area. The lack of plans and advisories for heat among populations is dangerous, as many previous studies suggest heat's impact on health and mortality is only expected to increase in the future (Greenough et al. 2001, Johnson and Wilson 2009).

Current heat warning systems (HWS) developed by the National Weather Service (NWS) and researchers, such as Laurence Kalkstein, work to identify "oppressive air masses" by measuring various meteorological elements such as: high and low daily temperatures, humidity, quantity of cloud cover, and wind speed (Kalkstein et al. 1996, Sheridan 2002). These measurements focus on the ambient, or felt, temperature to anticipate the negative impact on people by a city wide assessment. These heat warning systems are far from perfect, as they are difficult to compare amongst themselves or across climatic regions (Hajat et al. 2010). These warning systems are statistically able to predict weather events which facilitate an increase in mortality, but still contain a fair amount of unpredictability with respect to vulnerable populations (Johnson, Wilson and Luber 2009, Whitman et al. 1997).

Researchers believe that Kalkstein's unexplained variance is a result of diverse socioeconomic and environmental characteristics (Johnson et al. 2009, Naughton et al. 2002, Semenza et al. 1996, Whitman et al. 1997). Simply put, people experience an extreme heat event (EHE) differently depending on their living conditions. This is easily demonstrated by observing the dispersion of heat related illness and mortalities across large urban areas such as Chicago, IL. Therefore, new methods are needed to identify which neighborhoods and populations, within an urban environment, are at the highest risk during an extreme heat event. Previous studies have identified poverty, age, educational attainment, and race as variables which are predictive of heat vulnerability (Greenough et al. 2001, Cutter, Boruff and Shirley 2003, Johnson et al. 2009, Semenza et al. 1996, Whitman et al. 1997). While these variables have statistical support, they explain only a portion of the variance.

To improve the predictive modeling of vulnerable populations, environmental characteristics should also be included to improve the spatial specificity of heat warning systems (Cutter et al. 2003). Utilizing remote sensing systems, neighborhood land surface temperature (LST), and environmental features can help calculate the varying oppressive influences on residents across an urban environment (Johnson et al. 2009, Harlan et al. 2006). Improved spatially specific heat warning systems, such as these methods will describe, can provide city officials with the locations of neighborhoods which contain the highest vulnerability to heat waves, so aid and prevention projects can be planned in advance.

BACKGROUND

Researchers have long agreed that weather has an influence on the health of residents, particularly when extreme weather conditions are present. What is not as well known is how extreme weather conditions influence diverse populations. As the argument for global climate change continues, the ability to predict a distinct population's vulnerability during extreme weather conditions, such as increased temperature, will be crucial to preventing weather-influenced illness and mortality.

Previous climate models, such as those created by the National Weather Service (NWS), identify an extreme heat event (EHE) through measured deviations from normal temperature levels, over consecutive days. These models rely only on measurements of temperature and do not provide enough advanced or spatial warning, making them extremely outdated (Johnson 2009). More modern systems, such as those created by Laurence Kalkstein and his colleagues in the late 20th century, utilize multiple weather measurements for a "synoptic" analysis to identify repressive air masses. Kalkstein's model has become the new standard for predicting EHEs because it incorporates multiple weather measurements, recorded several times each day, to improve the predictive capability of his advanced weather warning system (Kalkstein 1991, Kalkstein and Davis 1989, Whitman et al. 1997). Kalkstein's Heat/Health Watch Warning System (HHWS) utilizes measurements such as: daily high/low temperature, wind speed, relative humidity, and cloud cover to predict a heat wave; it does not, however, consider the susceptibility of distinct populations (Johnson et al. 2009, Whitman et al. 1997). The model and design of Kalkstein's original warning system is still utilized in many cities and research projects, with minor adjustments to incorporate advances in technology, but improvements need to be made to improve its relation to vulnerability (Changnon, Kunkel and Reinke 1996, Ebi et al. 2003, Robinson 2001, Sheridan and Kalkstein 2004, Whitman et al. 1997, Harlan et al. 2006).

Whitman et al. (1997) credits Kalkstein for creating a weather model which contains the strongest air mass relationship to mortality, but suggests Kalkstein's HHWS does not account for all possible variance. Kalkstein himself claimed his methodology could be improved, stating, "The impact of weather upon mortality in summer is relative rather than absolute (Kalkstein and Davis 1989, 61)." This statement pertains not only to variances in regional and climatic zones, but also to the diversity found within a single urban environment (Hajat et al. 2010). Future warning models will require more than simple weather variables. Environmental and socioeconomic variables also need to be incorporated into future warning systems to improve predictability.

Harlan et al. (2006) developed a system known as the Human Thermal Comfort Index (HTCI), which incorporates spatial relationships to environmental stress, thermal variations, and vulnerable populations. Their methodology was designed to categorize compositions of vulnerable populations, believing that was the key to identifying which urban neighborhoods were at the greatest risk for heat-related illness and mortality. As has been presented in previous studies, heat waves do not affect communities uniformly across urban environments (Cutter et al. 2003, Harlan et al. 2006, Johnson and Wilson 2009, Johnson et al. 2009, Naughton et al. 2002, Semenza et al. 1999, Whitman et al. 1997). Rather, differences in the vulnerability of distinct communities, the result of unique physical and socioeconomic variations, cause different experiences of oppressive weather events (Cutter et al. 2003). Improved vulnerability warnings should be interdisciplinary and focus on identifying which populations are more vulnerable to weather disasters (Greenough et al. 2001).

Heat Warning Systems

Heat warning systems (HWS) are extremely important for reducing health risks during EHEs. Currently considered the deadliest weather-related phenomena in Northern America, and possibly the world, heat exacerbates preexisting conditions and is a "stealthy" or silent killer (Johnson and Wilson 2009, Davis 1997). Tornados, blizzards, and storms are the result of clouded weather fronts pushing into a region. Heat has no visible indication of encroaching danger, such as clouded storm fronts, without the utilization of meteorological equipment. This is one reason why the national government has mandated local NWS stations issue heat weather warnings (Ebi et al. 2004).

A heat warning from the 1995 EHE in Philadelphia, PA provided evidence on the benefits of a HWS by studying the predictability of mortalities. The study, conducted by Kalkstein et al. (1996), demonstrated how extreme weather events typically coincide with an excess of mortality; if properly forecasted, weather warning systems can prevent many of the excess mortalities though proper warning of the general public (Kalkstein et al. 1996, Ebi et al. 2003, Naughton et al. 2002). The Philadelphia 1995 HWS was deemed successful because studies of summer mortalities, post implementation of the HWS, identified a statistical decrease in the quantity of excess mortalities during a EHE. This was accomplished largely due to the increased quantity of public service announcements and civil services designed to warn and offer assistance to citizens during the event (Kalkstein et al. 1996).

Implementing a HWS can also be economically justified. Ebi et al. (2004) postulated that an increase in human survivability could be quantified monetarily to demonstrate how implementing a HWS could be more cost effective than allowing individuals to perish. Similar to how the Environmental Protection Agency (EPA) assigns a “value to life” during pollution studies, Ebi et al. (2004) quantified the value of lives which could be protected by heat warning systems. The EPA estimates the value of a single saved statistical life, based on the value of their projected income and assets, is near $6.12 million (Ebi et al. 2003). Ebi et al. (2004) studied the impact of weather warning systems on the age 65 and older population in Philadelphia, PA, and valued the life of an elderly individual to be $4 million. The HWS reportedly saved 117 lives in Philadelphia, PA over the course of three years, which equates to almost $468 million (Ebi et al. 2003). Estimating the cost of additional heat warning hotlines and emergency service crews would not exceed $10,000.00 per day, in an average city, the study suggests the cost of implementing a HWS is much cheaper than the cost of losing even a single life. The cost effectiveness of a HWS is further evident if the warning system was established as an internet based program. Through the internet, the system could automatically update current meteorological measurements and identify oppressive weather fronts without human interaction, reducing management costs (Ebi et al. 2003). Ebi et al. (2004) address a few alternative methods of assigning monetary value to life in their study, all of which based their analysis on mortality. The financial advantage of reducing hospitalization, due to heat stroke or dehydration, further demonstrates how fiscally beneficial the implementation of severe heat alerts and EHE preparation would be.

New advanced warning systems are needed, however, because alerts historically implemented by the NWS have shortcomings. Historical alerts do not factor in the cumulative impact of consecutive days of oppressive weather, account for the time of year, are not statistically related to morbidity, and cannot predict which populations are at the highest risk (Kalkstein et al. 1996, Johnson and Wilson 2009, Johnson et al. 2009). These are some of the reasons why the implementation of spatially specific warning systems, such as the one this thesis will demonstrate, could improve the protection of vulnerable populations beyond what current warning systems are able to (Greenough et al. 2001, Johnson and Wilson 2009). Improved warning systems are needed over increasing the quantity of warnings because improved systems will provide better identification of affected areas and less message fatigue. Shen et al. (1998) statistically demonstrated through a study of mortality during the 1995 EHE in Chicago, IL, that increasing the quantity of warnings, rather than improving them, decreases a warning's specificity and effectiveness. This is known as message fatigue. The inverse therefore suggests spatially specific warning systems would decrease the quantity of warnings needed, reduce message fatigue, and improve our understanding of vulnerability (Shen et al. 1998). Spatially specific HWS can allow city officials to utilize more intelligent preventative measures, directed at vulnerable areas. These improved warnings could decrease the number of lives lost, emergency crews needed, quantity of heat illness hospital admissions, and other costs associated with an EHE (Ebi et al. 2003, O'Neill, Zanobetti and Schwartz 2005, Shen et al. 1998). The impact natural disasters have on an area is dependent on the community's level of preparedness, therefore improving preparation can reduce a disaster's impact on local populations (Greenough et al. 2001). Documentation of vulnerable neighborhoods, derived from advanced spatial warning systems, could also be used to petition for disaster prevention funds. Federal disaster agencies, such as FEMA, provide such funds to communities looking to reduce the impact of weather related disasters (Greenough et al. 2001).

Vulnerable Populations

There has been a considerable amount of debate and research about which socioeconomic variables are related to EHE vulnerability. Previous research has demonstrated that the most prevalent include: age, economic level, race, level of education, and social isolation (Johnson et al. 2009, Johnson and Wilson 2009, Dolney and Sheridan 2006, O'Neill et al. 2005). Cutter et al. (2003) identified that some of the strongest associations with vulnerability are the age of the population and their economic situation.

Age can affect how an individual's body is able to adapt to inclement weather and maintain normal thermoregulatory processes. Age can also allude to the quantity of social interactions and pre-existing health conditions, all of which are documented as extremely important factors for surviving an EHE (Johnson and Wilson 2009, Cutter et al. 2003, Naughton et al. 2002, Whitman et al. 1997). An individual's economic status can also impact their vulnerability level. In a study conducted by McMichael et al. (2008), countries with a low or mid economic ranking were found to be have the highest risk to high temperatures. Economics can describe the amount of government aid needed, level of education or prevalence of less financially secure jobs. Economic indicators can also allude to the type of environmental impacts, such as age or condition of housing and amount of adjacent vegetation (Cutter et al. 2003). Having the ability to afford a well insulated residence or the ability or maintain a comfortable internal environment can be essential to surviving an EHE.

Economic Status

Economics have demonstrated a connection to EHE vulnerability, particularly for lower economic populations. Poverty is a variable which consistently shows up in vulnerable population studies (Changnon et al. 1996, Naughton et al. 2002, Johnson et al. 2009, McMichael et al. 2008). This is probably due to the overwhelming influence it has on other contributing vulnerability variables. People living in poverty typically have lower education attainment and take up residence in lower rent habitations, such as older buildings with less insulation or adjacent vegetation. Older buildings are harder to keep at an appropriate temperature and seldom have air conditioning (Davis 1997).

Air conditioning provides individuals with an artificial way of lowering the body's core temperature and preventing heat related illnesses. This is particularly true for elderly citizens and during early warm seasons when people have not properly acclimated to the heat (Changnon et al. 1996, Kalkstein and Greene 1997, Naughton et al. 2002, O'Neill et al. 2005). Some studies have reported a decrease in death risk between 50 and 80 percent when air conditioners are utilized (Semenza et al. 1996, Davis 1997). Evidence shows the availability of air conditioning, or the resources to use it, does positively correlate to the economic level of neighborhoods and could ultimately impact residents' survivability during an EHE (Dolney and Sheridan 2006). Inner-city populations without residential access to air-conditioning, relying instead on fans, are at a severe disadvantage. Fans provide a false sense of security to residents because they do not decrease the temperature, rather they only circulate air. When air is circulated by a fan sweat is removed from the body prematurely, reducing sweat's biological assistance in thermoregulation and can dehydrate residents faster. Davis (1997) cited a CDC study which suggested the utilization of fans had little impact on survivability when temperatures exceeded 100˚F, while air-conditioning improved survival by more than 50 percent.

Neighborhoods with economic stability and budgetary freedom should have a proportionally higher quantity of operating air conditioners during high temperature periods. This suggests that more economically advantaged areas are less susceptible to heat-related mortalities. Some current HWS utilize their media broadcasts to provide statistics on air conditioning costs to help poverty driven individuals understand how affordable air conditioning can be, and advocate residents to use the utility. Officials in more proactive cities have even mandated the return of disconnected utilities during an EHE to ensure residents having financial troubles can power available air conditioning units (Naughton et al. 2002). Lower income not only suggests there is less money for utilities, it also suggests there is less options for other methods of heat relief, such as membership to a pool or community center (Changnon et al. 1996).

Economics can also demonstrate how informed the population might be about inclement weather. In a study of the 1999 Chicago EHE, Naughton et al. (2002) recorded that the majority of people, 96 percent, learned about the heat wave through television programming. Lower income families may not possess a working television or other warning device, such as a radio or newspaper subscription, to warn them of the danger or level of heat expected in the near future. This is particularly relevant after the 2009 upgrade to digital television broadcasts. A household could have lost the function of their television if they were unable to afford the digital-to-analog converter, or if their television was unable to support it. Poverty, therefore, can also be an indicator of decreased warning of dangerous weather patterns.

Crime can also be a contributing factor in impoverished neighborhoods. Crime is positively correlated with poverty, as is violence. In high-crime neighborhoods, residents are less likely to migrate to cooler environments or open windows to regulate the temperature of their residence (Changnon et al. 1996). Lower income and crime are also representative of neighborhoods in which individuals have less stable jobs, lower educational attainment and increased government aid (Changnon et al. 1996).

Environment

Physical characteristics of neighborhoods are important to consider when predicting vulnerability to EHEs. Physical variability of the environment, such as presence of vegetation, between geographic locations can provide a direct indication of the oppressive weather (Luvall and Quattrochi 1998). Many previous HWS have not incorporated the environmental diversity found in large urban environments. Proximity to thermal exacerbating or cooling features has a strong influence on the local ambient temperature and risk level (Johnson and Wilson 2009, Johnson et al. 2009, Cutter et al. 2003).

Heat is one environmental variable which can be measured and documented quite efficiently between geographically distinct neighborhoods (Chen et al. 2006, Johnson et al. 2009, Li et al. 2004, Quattrochi and Luvall 1997, Voogt and Oke 2003, Weng and Quattrochi 2006, Zhang and Wang 2008). Differences in heat across urban landscapes are identified as an Urban Heat Island (UHI). An UHI represents how built materials, such as roads and buildings, interact with thermal electromagnetic energy; which can vary across an environment (Jensen 2007, Luvall and Quattrochi 1998). Built materials absorb and re-emit electromagnetic energy differently than vegetation. This causes distinct thermal strain on local populations (Chen et al. 2006, Jensen 2007, Luvall and Quattrochi 1998, Voogt and Oke 2003, Quattrochi and Luvall 1997). UHI impact is particularly noticeable during night hours (Chen et al. 2006, Zhang and Wang 2008). Built materials allow little relief from the heat as they continue to emit stored thermal energy throughout the night. This does not allow for normal diurnal temperature changes, making human thermoregulation more difficult (Sheridan 2002).

Previously thought of as a single (continuous or umbrella) variable for a city; recent UHI studies have demonstrated how influential diverse sections of the city can be to the UHI impact on residents. Improved spatial resolution of acquired thermal data can distinguish areas of increased surface temperature within urban environments (Luvall and Quattrochi 1998). The improved sensors document and demonstrate the presence of distinct micro-UHI (Johnson et al. 2009). These phenomena describe how different sections of the city experience different heat signatures or micro-climates. Neighborhoods categorized as “warmer” typically represent neighborhoods which are older and more densely built, or near heavily commercialized industrial zones which typically contain less vegetation. Both vegetation and built densities are proven to impact environmental temperature (Davis 1997, Cutter et al. 2003).

Mapping and identifying areas of increased UHI, derived from satellite imagery, provides a fixed variable for statistical study. Weather and temperature are normally unfixed variables, much like the before mentioned socioeconomic data, because they are constantly in flux depending on the time of day or season. However, utilizing data from a single point in time, such as a remotely sensed image, provides fixed variables which strengthen statistical analysis (Armstrong 2003).

In the study of residential vulnerability, conducted by Johnson and Wilson (2009), heat-related mortality was more concentrated in higher temperature residential areas, rather than vulnerable neighborhoods, during the 1993 Philadelphia, PA EHE. They identified the risk of heat-related mortality was highest in residential areas where vulnerable populations coincided with higher temperatures (Johnson and Wilson 2009). These results suggest including site specific temperature, socioeconomic, and environmental variables could produce more spatially specific warning systems than previously attempted. Identifying the most vulnerable areas would allow for intelligent planning of cooling stations and medical aid outposts during an EHE (Greenough et al. 2001).

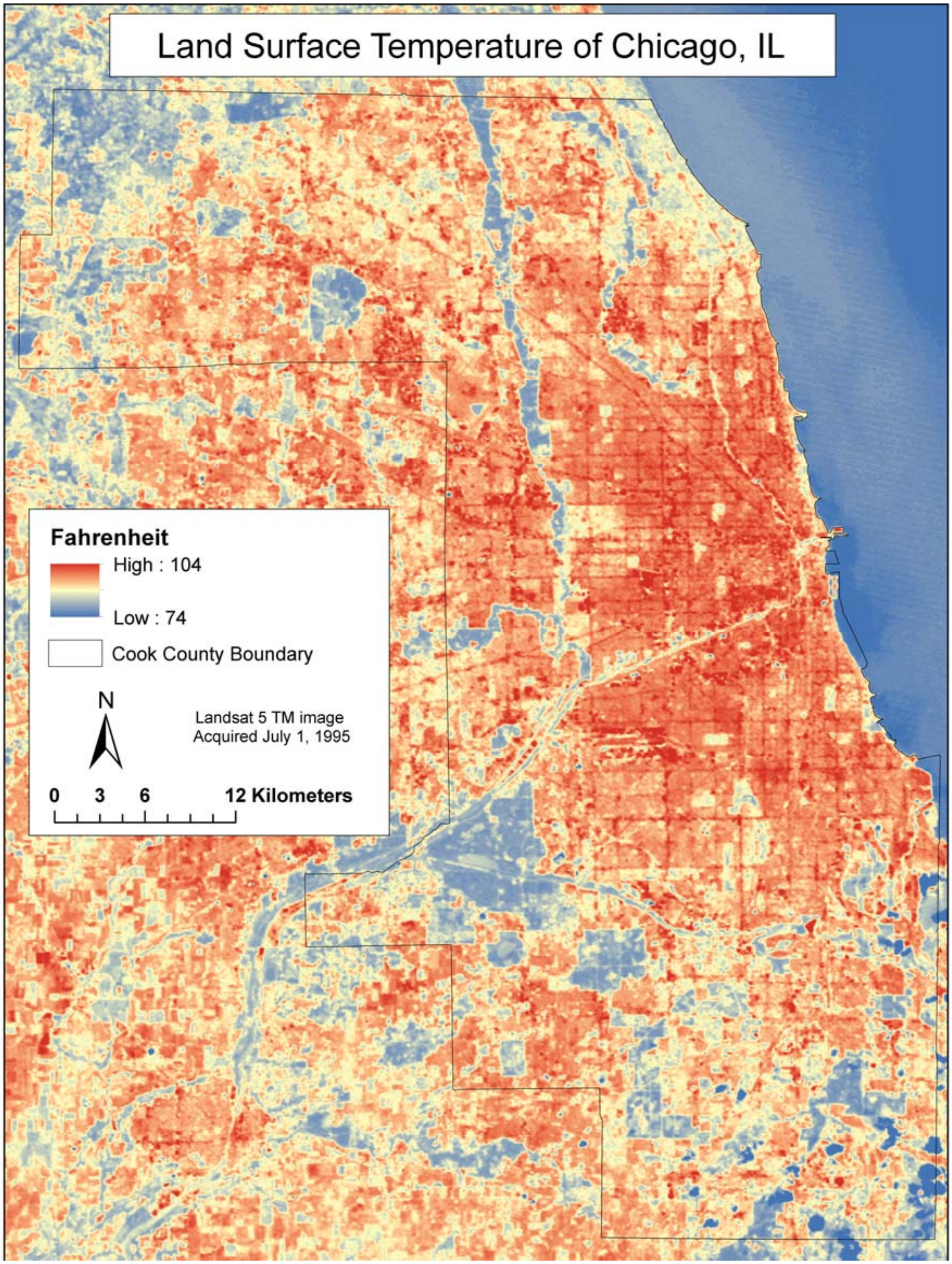


Figure 1: LST of Chicago, IL

Site specific temperature variables, or UHI, can be acquired through the utilization of thermal bands in satellite imagery, such as those acquired by the Landsat 5

TM. This data can be utilized to measure the intra-urban variations in LST or micro-UHI intensity. This is possible because the satellite collects electromagnetic information through wavelength specific receptors. The data is recorded by intensity values represented by digital numbers in its pixels, the sensor's smallest spatial data collection unit. Surface temperature can be calculated by converting the digital numbers recorded by the thermal wavelength receptors and correcting for atmospheric influences and surface emissivity (Qin, Karnielli and Berliner 2001). The importance of atmospheric correction is "to subtract the upward atmospheric thermal radiance and the reflected atmospheric radiance from the observed radiance at satellite level so that the brightness temperature at ground level can be directly computed (Zhang and Wang 2008, 7459)." The correction constants for Landsat data, which were used in this analysis, are well established and their utilization creates a more precise measurement known as "directional radiometric temperature" (Voogt and Oke 2003). The directional radiometric temperature incorporates the angle at which data is reflected from surface features and can be considered a measure of LST or Surface Urban Heat Island (SUHI) (Voogt and Oke 2003).

The thermal image utilized in this analysis was converted from digital numbers to temperature following the procedures outlined by Chander et al. (2009). The process converted at-sensor spectral radiance to at-sensor brightness temperature. This particular conversion used atmospheric correction and emissivity variables specific to the Landsat 5 TM satellite, so the resulting pixel values are considered to be a measure of surface temperature in Kelvin (Chander, Markham and Helder 2009). The procedures were conducted in ERDAS Imagine modeler, and contained an additional step to transform the output Kelvin value into a Fahrenheit temperature to improve reader comprehension.

When atmospheric and emissivity variability are considered, the at-sensor temperature value can be considered a measure of LST. Although ambient temperature and LST are not equivalent, they are related. Ambient temperature is a measure of weather impact on an individual. It is the combination of in situ collected meteorological measurements such as temperature, humidity, cloud cover, and wind magnitude. LST is a measurement of a surface feature's radiating thermal energy, how surface features interact with thermal electromagnetic energy (Jensen 2007, Li et al. 2004). Ambient temperature is affected by LST, but future research into emissivity "constants" are needed for researchers to better understand how emissivity changes across non-uniform environments, such as Chicago, before additional temperature measurements can be extrapolated by remote sensing devices (Johnson et al. 2009). Therefore LST provided the only meteorological variable in this analysis, representing the urban heat island (UHI), as its calculation methods are well established and supported.

Heat islands are typically best recorded at night (Voogt and Oke 2003, Chen et al. 2006, Zhang and Wang 2008). Nocturnal data is, however, difficult to work with as the only sensors available to collect nocturnal images are either too expensive, such as aircraft based sensors, or do not contain the spatial resolution required, such as the MODIS satellite, to adequately analyze this type of project. Nocturnal data can also contain misleading data, such as water's high energy threshold, which is a natural cooling feature during the day but shows high nocturnal thermal properties (Jensen 2007). For the project at hand, data collected by the Landsat 5 TM can provide an accurate assessment of LST to identify UHI variation across the Chicago, IL landscape. Combining the thermal data with other remotely sensed indexes available for acquisition only during day hours, such as vegetation data, can improve the understanding of environmental influence of vulnerability (Voogt and Oke 2003).

Vegetation is a natural cooling feature for the environment, so the presence and density of vegetation can greatly impact an area's thermal loading (Luvall and Quattrochi 1998, Quattrochi and Luvall 1997, Voogt and Oke 2003, Chen et al. 2006). Davis (1997) stated, "outdoor summer temperatures are dramatically reduced by the abundance of shade trees (Davis 1997, 38)." Therefore the quantity of vegetative influence on the local environment is a powerful environmental variable to consider. A Normalized Difference Vegetation Index (NDVI) can be utilized to provide a vegetation variable. The NDVI is typically used to analyze the health of known vegetation areas, by analyzing leaf structure and water content, but can also be used as an indicator for vegetation presence and density (Zhang and Wang 2008). The NDVI is an index ratio between the value of Near-Infrared and Red bandwidths of the electromagnetic spectrum collected by a sensor's pixels using the following formula:

$$\text{NDVI} = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$$

It utilizes the relationship between the absorption of red visible light, used for photosynthesis, and the reflection of N-IR energy to determine a leaf's health (Zha, Gao and Ni 2003, Jensen 2007, Li et al. 2004, Zhang and Wang 2008).

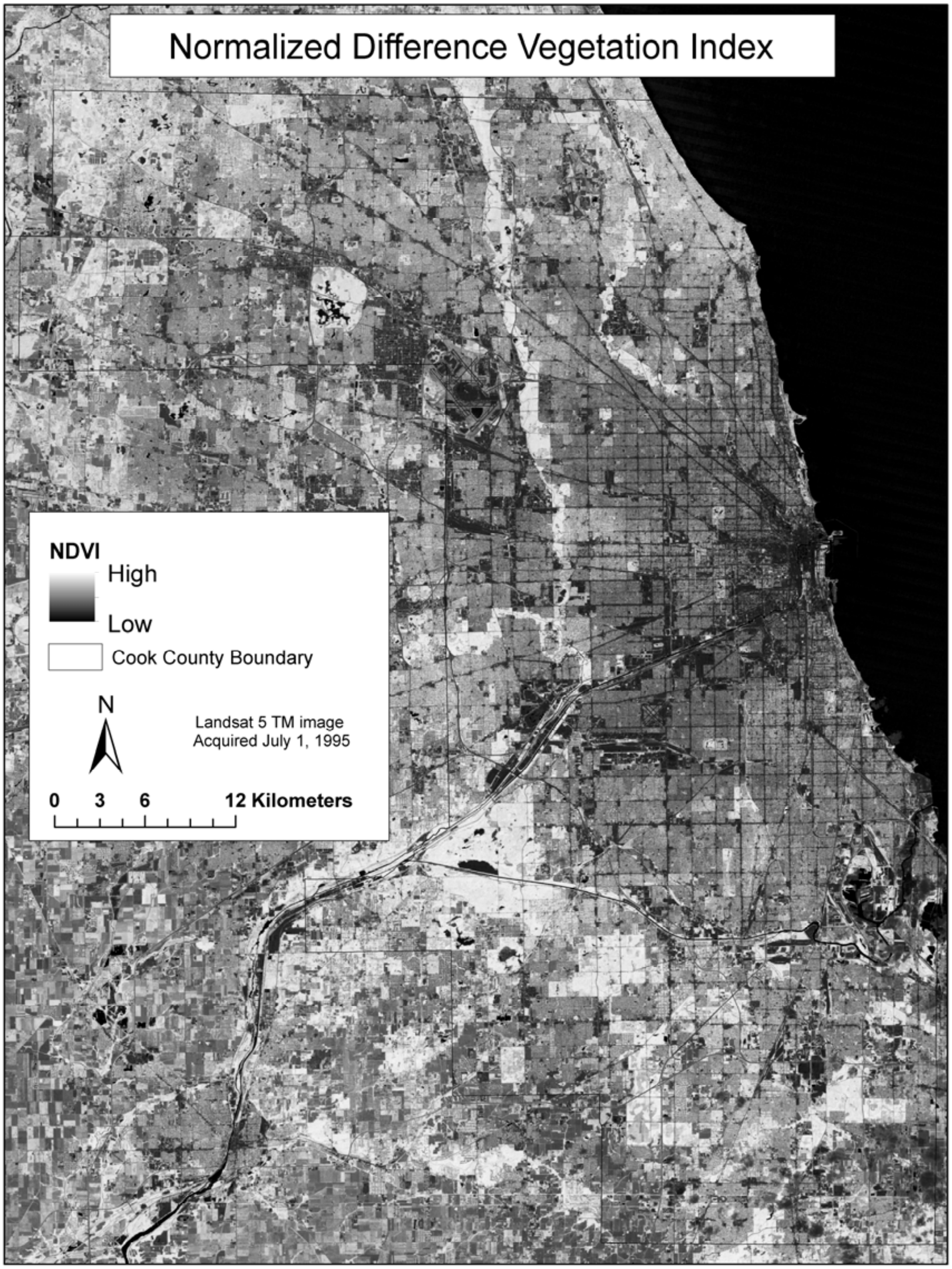


Figure 2: NDVI of Chicago, IL

The Normalized Difference Built-up Index (NDBI) describes the density of built environment by utilizing a ratio of the Mid-Infrared and Near-Infrared electromagnetic spectrums (Jensen 2007, Zha et al. 2003). The formula for NDBI is as follows:

$$NDBI = \frac{\rho_{mir} - \rho_{nir}}{\rho_{mir} + \rho_{nir}}$$

In a study conducted by Zha et al. (2003), the NDBI's ability to accurately differentiate between built features and other environments was over 92 percent. This accuracy is far superior to computer driven unsupervised classification processes and comparable only to human classification methods, but much more cost and time effective. This index is typically transformed into a binary variable, built or not, but can be retained in its calculated index form to emphasize areas of built-up density. This index can also be used as a check for UHI, as it highlights many of the same areas, due to the built environment's affect on LST. One slight drawback of using the NDBI is the mid-IR electromagnetic energy used in its calculation is also highly reflected by bare soil. Therefore, when utilizing the NDBI the scope of view should be restricted to city limits where limited bare soil is present (Zha et al. 2003). The presence of bare soil did not impact this study, because Chicago, IL is very urbanized. What little bare soil is present in the city is typically found in construction sites, which do not remain barren for long.

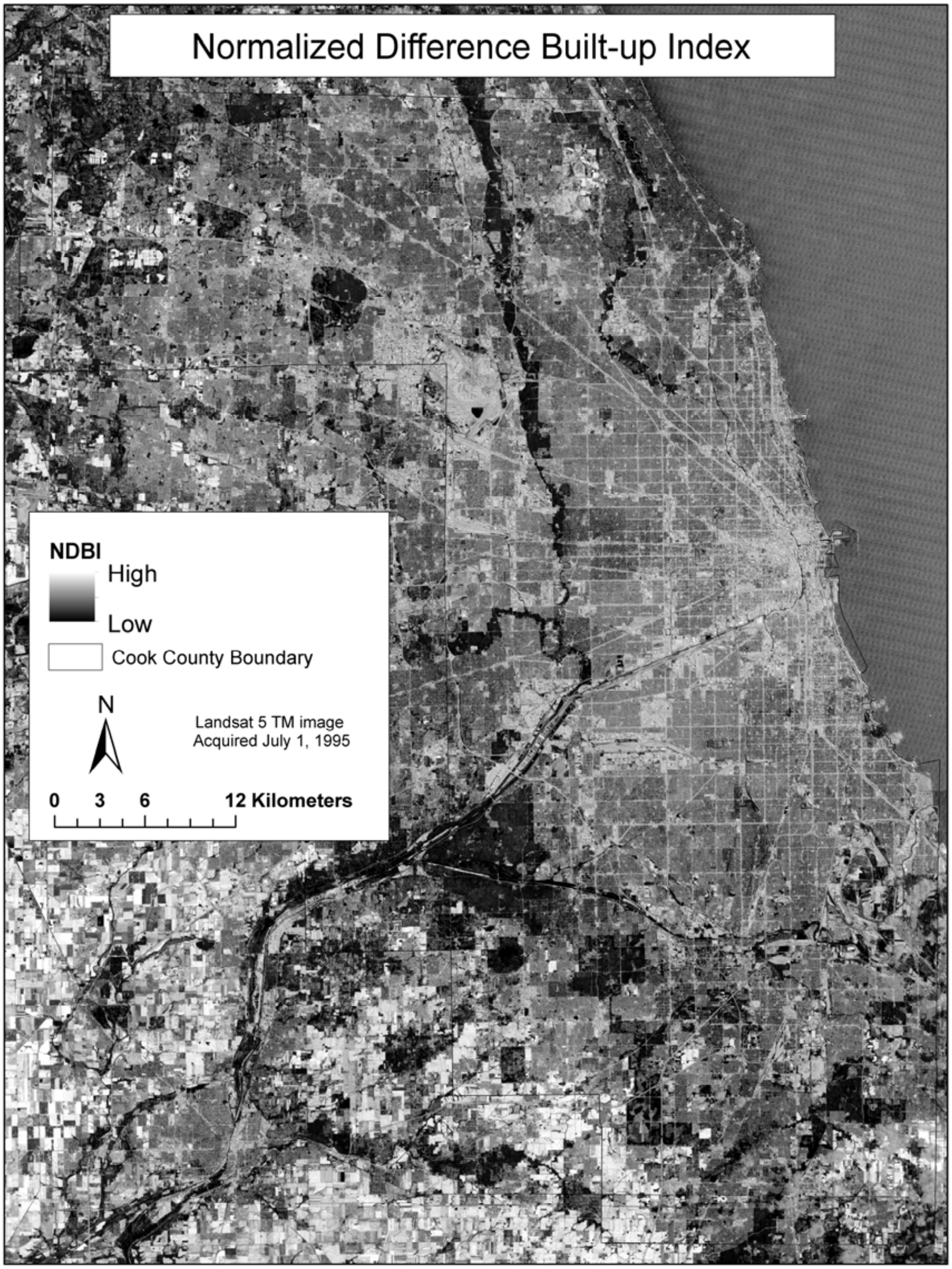


Figure 3: NDBI of Chicago, IL

Age

Whitman et al. (1997) estimated more than 70 percent of the heat-related deaths during the Chicago, IL 1995 heat wave occurred in the 65 years of age or older population, an observation supported by many other researchers (Changnon et al. 1996, Ebi et al. 2004, Dolney and Sheridan 2006). Age has been considered a significant vulnerability factor because it can represent many conditions which exacerbate vulnerability, such as: financial status, pre-existing medical conditions, and social isolation. A majority of old and retired individuals are on a fixed income, a financial aspect of increased risk among the elderly (Changnon et al. 1996). Age can also be viewed as an indicator of self sufficiency and an individual's ability to adapt to changing or dangerous environments (Cutter et al. 2003, Naughton et al. 2002).

Pre-existing medical conditions can make individuals more vulnerable to natural disasters. The prevalence of diabetes and cardiovascular diseases are some of the physical conditions that can lead to increased risk during an EHE (Dolney and Sheridan 2006, Changnon et al. 1996). Census data does not provide a measure of chronic illness, but does include variables for age. Age can provide an indication of health since many chronic diseases, and pre-existing illnesses, are more prevalent among older generations (Robinson 2001, Schwartz 2005, Semenza et al. 1996, Shen et al. 1998, Centers for Disease Control 2002, Centers for Disease Control 2006). Pre-existing conditions cause damage to important organs and increase the risk of heart attack or stroke during natural thermoregulatory processes (Centers for Disease Control 2002). To release body heat, blood vessels dilate and expand against the skin, a process known as vasodilatation, which lowers blood pressure and forces the heart to beat harder (Centers for Disease

Control 2002). The additional pressure can increase the risk of heat stroke, cardiovascular complications, and death (Kalkstein and Davis 1989). Semenza et al. (1999) calculated that cardiovascular symptoms accounted for 67 percent of the inpatient hospital admissions of individuals aged 65 and older during the 1995 Chicago EHE. This number is 4 percent higher than during their control year, indicating an increased risk of cardiovascular complications during the EHE (Semenza et al. 1999).

There are also many mental or cognitive conditions that can affect an individual's risk, particularly amongst the elderly population (Johnson and Wilson 2009, Centers for Disease Control 2002). Loss of cognitive processes, such as from Alzheimer's disease, can make it difficult for individuals to accurately assess their situation and risk. Loss of sensory sensitivity can similarly create a false sense of comfort in hazardous weather situations. Elderly men have been known to exhibit a reduction in thirst sensation, which can cause less than adequate hydration practices (Semenza et al. 1999). Neurological and physical handicaps, such as Parkinson's disease, can reduce an individual's ability to relocate to cooler environments or acquire fluids (Centers for Disease Control 2002, Centers for Disease Control 2006). Semenza et al. (1996) documented an increased risk of 16 percent for patients who were confined to bed and a mortality rate six times greater for those who required the services of a visiting nurse. Individuals living alone or with limited social interaction also demonstrate an increased risk of heat related illness, as there is no one to monitor their health or offer assistance if they start to experience heat induced symptoms (Changnon et al. 1996, Naughton et al. 2002, Centers for Disease Control 2002, Centers for Disease Control 2006).

Diabetes, obesity, and many other physical or mental disabilities can be present in any age demographic. The study conducted by Naughton et al. (2002) alluded that mental illnesses among middle-aged populations has an adverse affect on survivability, just as it does with the elderly population. This suggests that any individual has an increased vulnerability to heat when they have a physical or mental ailment (Semenza et al. 1999, Semenza et al. 1996). Statistically, however, the age groups of "5 and younger" and "65 and older" are at a higher risk for chronic diseases, which is why they are the age variables utilized in this type of study (Changnon et al. 1996, Cutter et al. 2003, Dolney and Sheridan 2006, Ebi et al. 2003, Johnson and Wilson 2009, Johnson et al. 2009, Semenza et al. 1996).

As just mentioned, elderly are not the only increased risk age demographic. Children age 5 and younger have also been documented as being more vulnerable to climatic extremes (Johnson and Wilson 2009, Dolney and Sheridan 2006, Centers for Disease Control 2002). Young children may not understand how to maintain proper levels of hydration, that their play should be less physically demanding, or that they should relocate to a cooler environment during extremely hot days (Centers for Disease Control 2002). Furthermore, many young children may not have the mobility necessary to relocate to cooler locations. Even if a child's motor skills would allow them to move between rooms, they may not be able to extradite themselves from a house with inclement temperature, or may be thwarted from doing so by a monitoring parent. An environment suitable for an adult could be dangerous for a small child, whose body does not maintain the same level of fluids. Mild fevers induced by increased environmental heat can quickly progress to heatstroke in infants if left unchecked (Centers for Disease Control 2002).

Studies suggest that socialization among people of any ages is very beneficial to survival rates. Naughton et al. (2002) reported that there were no heat related mortalities among children aged less than one year during another Chicago, IL heat wave during 1999. The study suggested that increased social interaction, particularly in air conditioned public buildings such as day cares or preschools, was responsible for the decline in susceptibility from previous studies (Naughton et al. 2002, Semenza et al. 1996, Semenza et al. 1999). Elderly people with pets requiring walking had similar reductions in vulnerability as neighbors could notice their absence, or ailments from the heat (Semenza et al. 1996). It can be assumed that interaction and monitoring higher risk individuals of any age is crucial for their survival.

Medical Impact of Heat

Researchers have used different variables when determining the affect heat has on people's health. Semenza et al. (1999), and Dolney and Sheridan (2005) have suggested hospitalization or ambulance records could provide a larger quantity of heat illness incidents for analysis. Medical records, however, can be difficult to acquire and organize. Patients requiring transfers between ambulance services or medical wards can further complicate the issue if their transfer is for a different medical purposes than their arrival indicated. Mortality, on the other hand, demonstrates the most extreme or severe condition which spatially specific warning systems should focus on preventing.

Johnson and Wilson (2009) used mortalities from the 1993 heat wave in Philadelphia, PA to analyze vulnerability. Semenza et al. (1996) similarly used death certificate data for their case study of the 1995 EHE in Chicago, IL. The method of utilizing mortality provides a binary class system, affected or not. This process simplifies the interpretation of results compared to other medical reports such as hospital records or 911 medical emergency calls (Sheridan and Kalkstein 2004).

Documentation of heat related mortalities is not without problems, however, as there is no explicit nor standardized criteria for heat related death between autopsy offices (Changnon et al. 1996, Shen et al. 1998, Centers for Disease Control 2002, Donoghue et al. 1997). For a death to be considered heat related the deceased body has to pass a few generalized criteria during autopsy. In general, the measured body temperature must be 105˚F or higher at the time of death, there must be evidence of high environmental temperature at the scene of death, the body must be in the process of decomposition, and the individual must have been last seen alive during the heat wave period (Whitman et al. 1997, Donoghue et al. 1997, Shen et al. 1998). The National Association of Medical Examiners Ad Hoc Committee utilizes similar methodology for defining heat related mortalities, adding the requirement that evidence of trauma, fatal injury, or toxin must be ruled out. They also require the presence of high ambient temperature at the location of the demise must be recorded, not simply mentioned, in order to facilitate a heat related mortality (Donoghue et al. 1997). Whitman et al. (1997) stated that the Cook County Medical Examiner's Office appropriately documented a death as heat related, during the 1995 EHE, if there was no history or evidence of trauma or fatal injury (Shen et al. 1998).

During the July 1995 EHE, Chicago experienced an increase in mortalities of 31 percent from similar time periods in previous years (Whitman et al. 1997). It was the largest proportional increase of mortality Whitman et al. (1997) were able to locate on record. Semenza et al. (1996) included deaths resulting from cardiovascular complications in their study of the 1995 Chicago, IL EHE if heat was listed as a contributing factor to the mortality. This was done because heat has a strong influence over cardiovascular systems and complications, as previously mentioned, can easily occur which can result in heart attacks or strokes (Shen et al. 1998). Other physical and neurological illnesses, such as diabetes or Parkinson's disease, also make individuals more prone to heat illnesses. It can therefore be noted that heat is not only a dangerous entity on its own, but exacerbates preexisting conditions. If heat maintains such a strong influence on pre-existing conditions, then dividing mortalities into medical subgroups would not create an improved description of risk during an EHE (Schwartz 2005). Kalkstein and Greene (1997) wrote, "Recent analyses indicate that a wide range of causes of death are impacted by weather, which suggests that disaggregation of mortality causes will not necessarily lead to improved relationships [to death] (Kalkstein and Greene 1997, 87)." Shen et al. (1998) reported that many of the estimates of heat mortalities from the Chicago, IL 1995 EHE were underestimated because mortalities caused by pre-existing health concerns, such as cardiovascular and respiratory diseases exacerbated by heat waves, were not included in the mortality counts. It should therefore be assumed that utilizing all mortalities which listed heat as a contributing influence, or any cardiovascular complication would not overestimate the influence of heat on the mortality count during an EHE.

According to Semenza et al. (1999), incidents of crime or mishap did not increase during the 1995 EHE in Chicago, IL. Therefore, the removal of all criminal, violent, or accidental deaths from mortality records results in a list which contains mortalities of individuals who would have perished during the heat wave anyway, those directly related to the influence of the EHE, and individuals who were so ill they would not have survived anyway; a term known as Mortality Displacement (Kalkstein and Greene 1997). A study which includes all mortalities which could have been caused by thermal influence should best represent the medical impact of an EHE. This includes, but is not limited to, deaths caused by cardiovascular, cerebral vascular complications, or respiratory disease when heat is listed as a contributing factor and there is no evidence of violent trauma or toxic substances.

METHODS

Environment

The area of focus for this study was Chicago, IL, USA during the July 12 through 16th, 1995 EHE (Semenza et al. 1996, Whitman et al. 1997, Semenza et al. 1999). It is located in northeast Illinois, bordering the southwest portion of Lake Michigan. Chicago is categorized as a humid continental climate, which has four distinct seasons and an average daily July temperature of 75.56˚F. The daytime temperature during the 1995 heat wave, according to the National Climatic Data Center, ranged between 86.06 and 104˚F. During this time period, the low temperature never got below 73.04˚F. This time period is well documented as an EHE, so no analysis of weather conditions was required for these proceedings (Centers for Disease Control 1995, Shen et al. 1998, Naughton et al. 2002). The terms Chicago and Cook County were considered to be interchangeable through this analysis, but refer to the area defined by the Cook County boundary where all variables were extracted for this

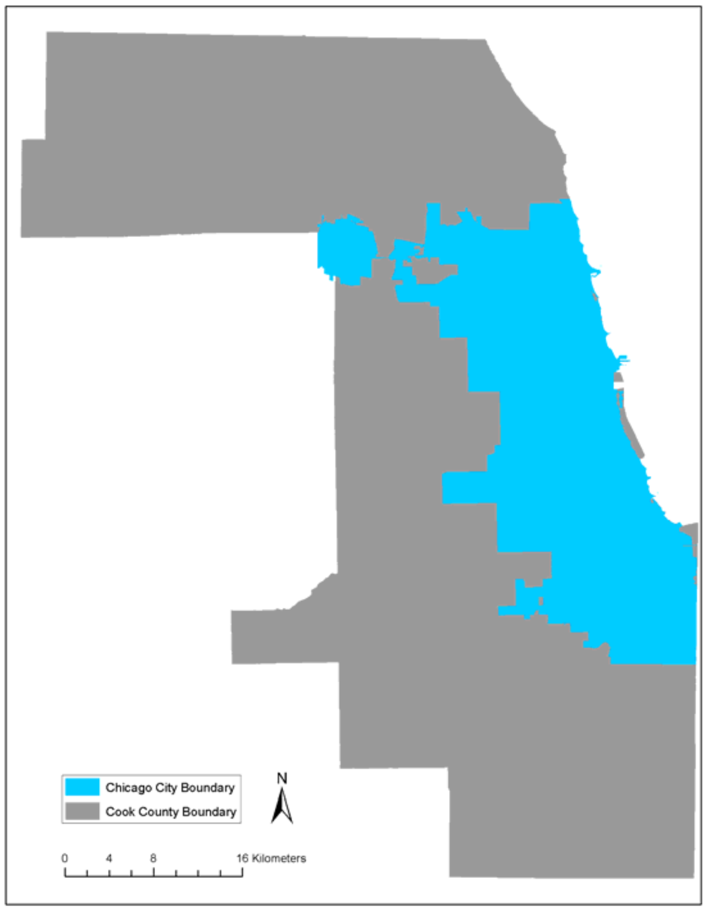


Figure 4: Cook County and Chicago City Boundaries

analysis. The county boundary was used because it incorporated more area, reduced edge confounding errors within the city limits, and provided a better examination of environmental features.

Spatial Resolutions of Analysis

This analysis focused on residential areas, where it was assumed people spent the majority of their time during the 1995 EHE. Three boundary layers were used to compare the boundaries' ability to calculate vulnerability. The boundary designations included: political boundaries, land use classification areas, and building zone identification codes. Each boundary was tested at two spatial resolutions to test the importance of spatially specific data. If smaller spatial boundaries were found to be more predictive, it would demonstrate the importance of using improved spatially specific data collection methods and variables for vulnerability assessment.

The simplest and primary boundary layer for the analysis was provided by census data's political boundaries, representing the census tract and block group datasets. These primary levels of analysis provided the first test of the spatial resolution's impact on vulnerability, and also provided a guide for the other boundary layer resolutions. The census tract and block group political boundaries vary in size, even amongst themselves, because their shapes and sizes are distinguished by population. Since adjacent political boundaries are marginally equivalent in population sizes, the political boundaries also provided a control on population density. Census boundaries do not contain any environmental variables, but their unique ID code was used to maintain a consistent label for all boundary resolution tests. The political ID enabled the two spatial distinctions of larger and smaller resolution acquisition, census tract and block group respectfully, to remain consistent between all boundary trials. This was accomplished by assigning the political boundary IDs to the remaining boundary layers through Arcmap's spatial join feature.

The second boundary layer was created through the utilization of the U.S. Geological Survey (USGS) National Land Cover Dataset (NLCD) map. The map provided an unbiased distinction of environmental features, because the feature classifications for NLCD maps are identified and distinguished using unsupervised classification remote sensing techniques. This process was accomplished by using Landsat 5 TM satellite imagery, circa 1992, to compare the spectral signatures of diverse land features (USGS 2010). Signatures which are mathematically similar are grouped together into classes. This process is considered unbiased because it utilized limited human influence on the identification of distinct land cover classes. This procedure produced two residential areas, identified as classes twenty-one and twenty-two, low and high density residential areas respectfully. Low density residential refers to areas of low building densities with space for vegetation, such as you would find in residential neighborhoods comprised of single family dwellings. High density residential features are defined as areas with closely built houses and multi-family residential complexes, such as small apartment and condominium complexes, with less vegetation present (USGS 2010). This boundary layer allowed for the removal of large industrial and commercial areas which could impact the UHI of adjacent residential areas. It also removed the cooling and protective element of parks, forests, and water systems. Water and vegetation have high thermal properties, which can impact LST (Zhang and Wang

2008). Therefore, removing the areas adjacent to residential neighborhoods provided for a study which incorporates only the residential impact of environmental variables, such as LST. This is acceptable because the parameter of this study was to examine the impact environmental characteristics had on residential areas.

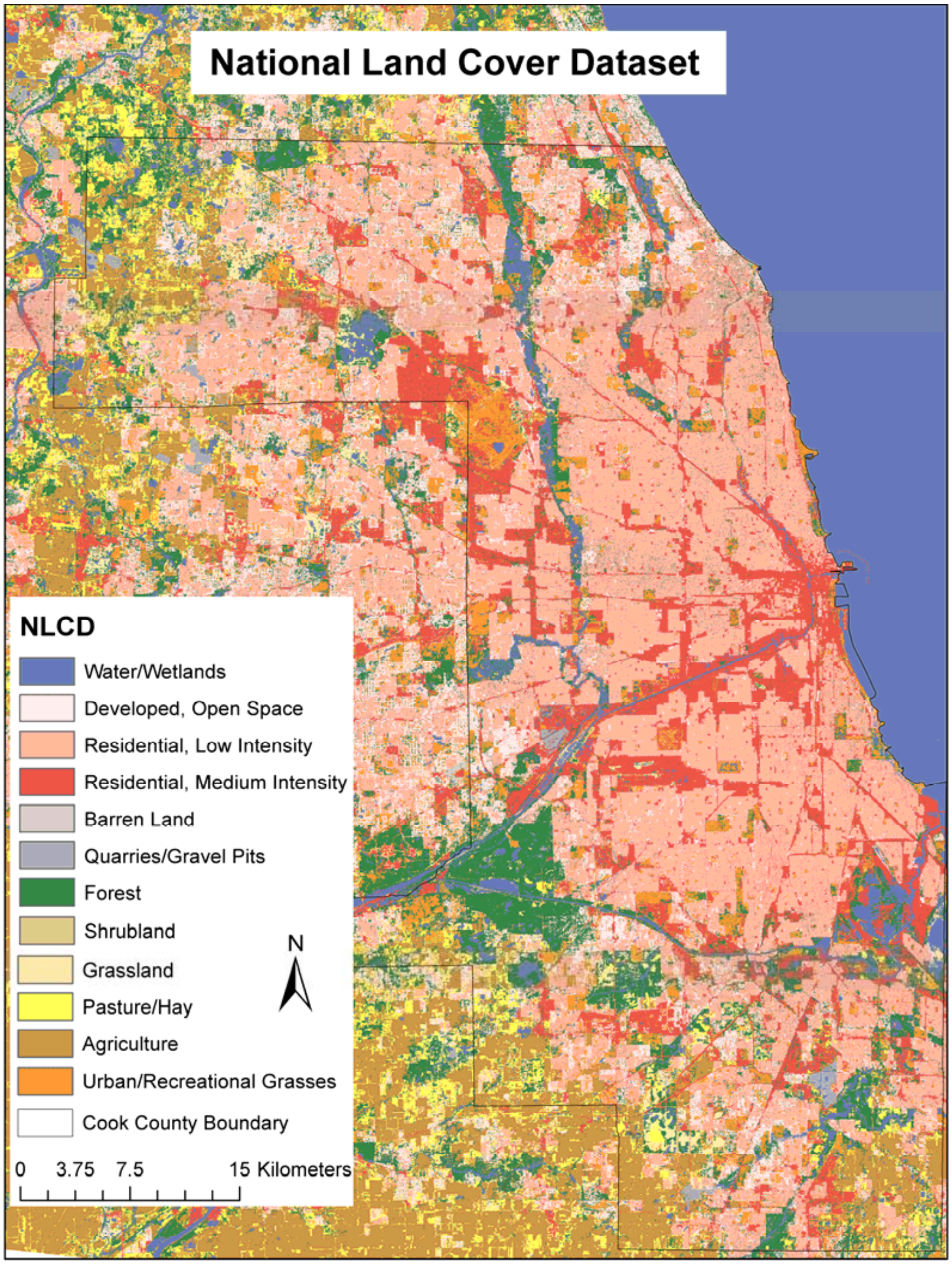


Figure 5: USGS NLCD map

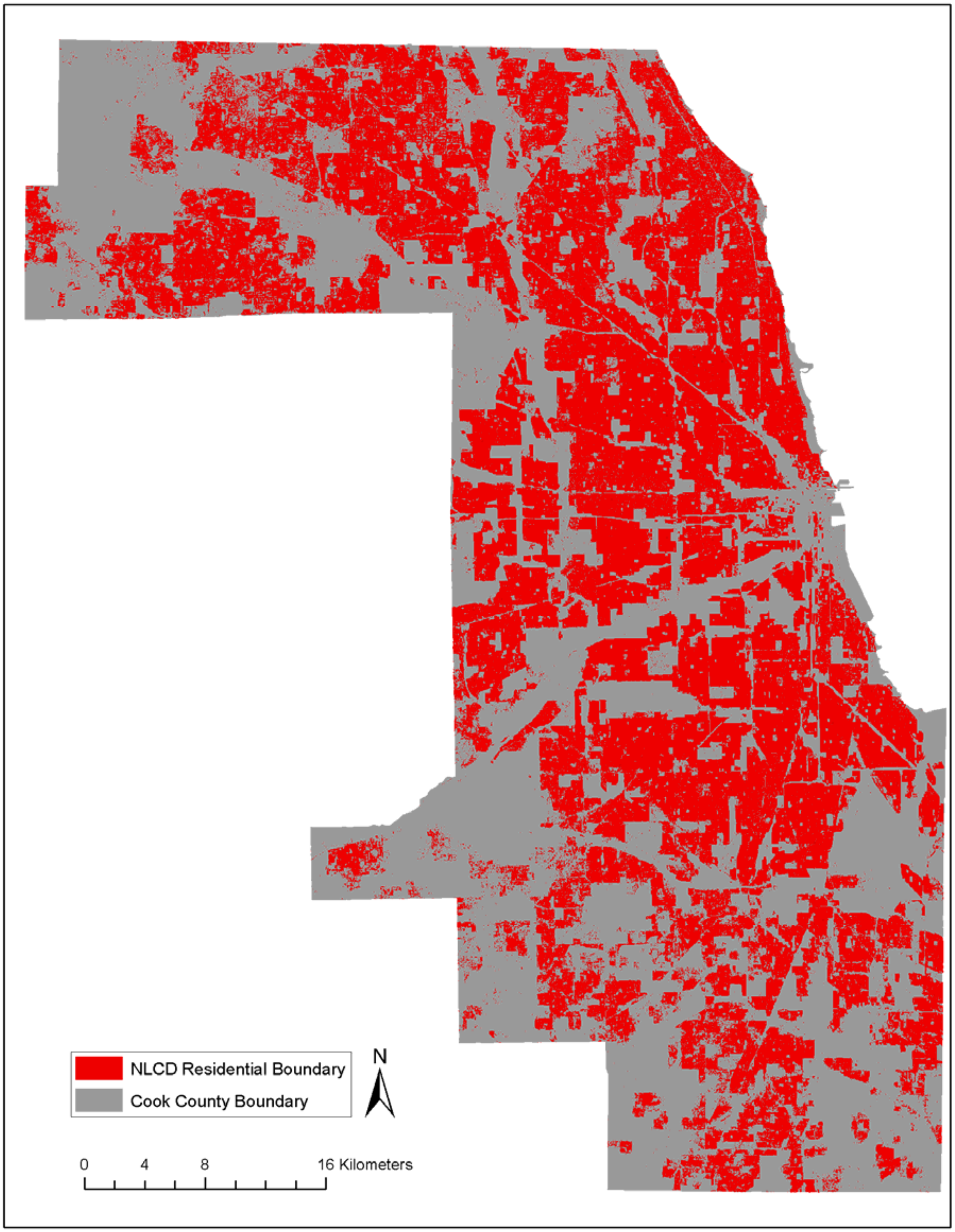


Figure 6: USGS NLCD Residential Boundaries

Because Chicago allows for mixed commercial and residential buildings, the NLCD residential boundaries might not have included all possible residential features.

Utilizing areas designated as class twenty-one or twenty-two removed commercial and industrial areas, but may have also removed areas of mixed residential/business use, such as large high rise apartment complexes or mixed residential/commercial land. This is because the spectral signatures of these areas are similar to heavily developed commercial areas. The inclusion of mixed business and residential features were considered during the third analysis utilizing building zone IDs.

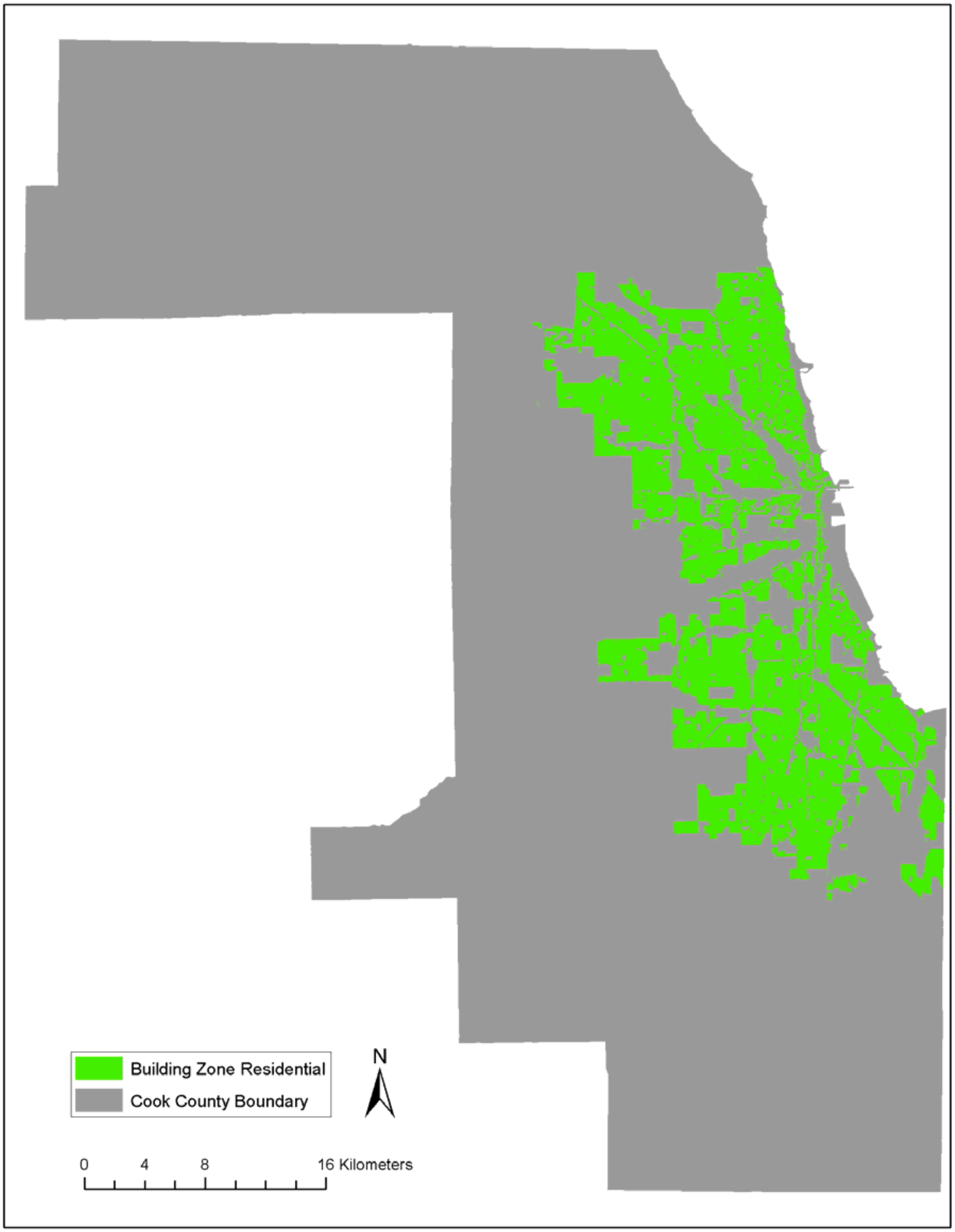


Figure 7: Chicago Building Zones coded for Residential use

Building codes, or zone IDs, are an identification tool utilized by government officials to distinguish potential uses for buildings. Because Chicago allows for the mixed use of buildings, such as residential dwellings above ground level businesses, this boundary utilized any building code which allowed for residential use. This process provided a more residentially focused analysis than the NLCD boundary previously mentioned, by ensuring all residential areas were included.

Residential areas identified by the NLCD raster and building codes were converted into polygon shapefiles through ArcMap's toolbox at each of the political boundary resolutions. This was so they could become indicators of residential areas within the political boundary. This enabled a continuation of the resolution test and provided a more consistent spatial dynamic to reduce confounding errors associated with utilizing different types of boundaries. The spatial joining to political boundary resolutions allowed for the extraction of environmental variables at unique residential designations, while retaining the use of the political IDs and population density control provided by the census boundaries. Focusing only on residential areas assured the environmental variables, such as UHI, were not affected by industrial complexes which may be present within a political boundary. This is an important step because the presence of heavily commercialized or industrial areas increases UHI and temperature, imposing an indirect negative environmental impact on the area. Utilizing only residential areas should have provided a better indication of the environment within residential neighborhoods which have a direct impact on residents.

Heat Mortalities

Mortality data was used to provide a binary and spatially specific variable which could be used to spatially compare documented areas of mortality with predicted vulnerability from the statistical output. The mortality data was acquired from a previous study conducted by researchers at Wright State University. With approval from the Institutional Review Board, those researchers received copies of death certificates from the Illinois State Department of Health, created during the 1995 EHE, to identify locations of people affected by the heat. Using the residential addresses from the death certificates, mortalities were geocoded into an Arcmap shapefile at an accuracy level above acceptable parameters. For this analysis, the mortality data was spatially joined to the boundary polygon shapefiles to provide mortality count variables for each trial. These generalized mortality counts, rather than the original data and locations, were used for analysis and display in this report to protect the identity of specific households, families, and individuals who were affected by the heat wave.

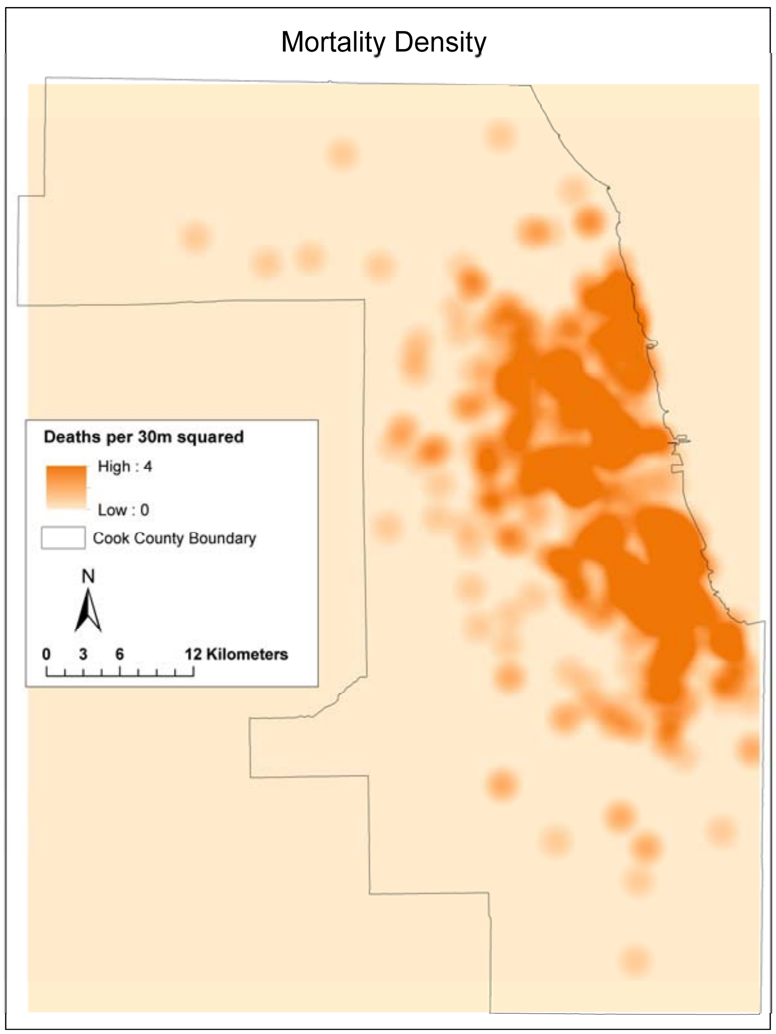


Figure 8: Heat Mortality Density

The generalized data maintained enough spatial specificity to continue the analysis. The mortality data was used for two purposes, firstly for visual comparison of highly vulnerable areas with a mortality density map, which can be seen by Figure 8. The second purpose was to quantify the amount of mortalities which occurred in each predicted vulnerable risk level. This provides a documentation assessment on whether the specific procedures outlined in this study could be used for a HWS. If the proposed vulnerability risk level increases congruent with the quantity of mortalities occurring in those designated areas, the validity of this study's model can be documented.

Heat related mortalities were identified through the cause of death information provided by the death certificates. The criteria used to identify heat mortalities was designated by The National Association of Medical Examiners Ad Hoc Committee and the Cook County Medical Examiner's office. Heeding the advice of Shen et al. (1998) and Semenza et al. (1996), mortalities caused by cardiovascular, respiratory, or any other pre-existing medical condition remained in the database if heat was listed as a contributing factor and no evidence of trauma or toxic substances was recorded. Violent and toxin related mortalities were removed from the dataset to improve the spatial analysis between heat and death. Removing non-weather related mortalities was considered an act of isolating the EHE impact, as the quantity of violent and accidental deaths did not increase, from the city's average, during the heat wave (Semenza et al. 1996). It is therefore assumed the quantity of violent deaths were not affected by the temperature (Semenza et al. 1996). The methodology of retaining the remaining health caused mortalities is supported by many researchers who reported heat exacerbates pre-existing medical conditions, and removing chronic illness cases would have underestimated mortality caused by the heat wave (Donoghue et al. 1997, Johnson and Wilson 2009, Whitman et al. 1997, Shen et al. 1998).

More than 700 mortalities were documented during the 1995 EHE. However, only 586 qualified as heat related by the above mentioned conditions and were utilized for this study. All 586 documented mortalities are a reliable estimate of heat-related mortality for the EHE. Multiple research projects have examined the criteria used by the Cook County Medical Examiner's Office during the 1995 EHE, and concluded the number of heat related mortalities were not overestimated (Whitman et al. 1997, Centers for Disease Control 1995, Shen et al. 1998).

Other studies have removed the mean level of death during the season, examining only the quantity of increased mortalities believed to be directly related to the EHE (Kalkstein and Greene 1997, Kalkstein et al. 1996, Semenza et al. 1999). Such methods can prove influential for studying the statistical influences of an EHE, but this study required analyzing the spatial location of death. There is no way to distinguish, from the death certificates, between individuals who would have normally died during this time period and those impacted by the heat wave, a term known as mortality displacement. Therefore determining and analyzing the physical locations of "excess" mortalities is impossible, any attempt to do so would provide inaccurate and unreliable results. This study retained all mortalities designated as heat-related. This methodology is supported by Sheridan and Kalkstein (2004), who reported it is better to include rather than remove contributing causes of death, particularly since heat mortality has not been appropriately standardized (Sheridan and Kalkstein 2004).

Vulnerable Populations

Vulnerability has been identified through the statistical testing of socioeconomic and environmental data in many studies. Socioeconomic data for this analysis was acquired though decadal census data, collected by the U.S. Census Bureau. Although financial and demographic variables are typically considered to be non-static, consistently changing levels and locations over time; census data represents the variables at a specific time, providing fixed variables to improve and strengthen the robustness of statistical processes (Armstrong 2003). Population socioeconomic data used for the identification of vulnerability in this study was assembled from the 1990 census. Based on the parameters of previous vulnerable population studies, such as those completed by Cutter et al. (2003) and Harlan et al. (2006), vulnerable variables included parameters for: age, economics, education, and race. A full list of the variables can be viewed in Table 1. Median Family Income (MFI), Medium Household Income (MHI), Per Capita Income (PCI), educational attainment, and poverty were used to demonstrate economic trends across the urban environment (Johnson et al. 2009, Cutter et al. 2003). Age variables were also extracted from census data and included variables for: age 5 and younger, age 65 and older, and age 65 and older living alone.

VARIABLE	DEFINITION
American Indian pop	Total population: American Indian and Alaska Native alone
Asian pop	Total population: Asian alone
Below Poverty	Population for whom poverty status is determined: Income in 1989 below poverty level
Black pop	Total population: Black or African American alone
Female age 5 & under	Population 5 years and younger: Female
Female age 65 & up	Population 65 years and over: Female
Female age 65 & up living alone	Population 65 years and over: In households; In nonfamily households; Female householder; Living alone
Female HS Degree	Population 25 years and over: Female; High school graduate (includes equivalency)
Female no HS Degree	Population 25 years and over: Female; Educational attainment; below high school
Hawaiian pop	Total population: Native Hawaiian and Other Pacific Islander alone
Hispanic pop	Total population: Hispanic or Latino
LST	Land Surface Temperature derived from Landsat 5 TM imagery acquired July 1, 1995
Male 5 & under	Population 5 years and younger: Male
Male age 65 & up	Population 55 years and over: Male
Male age 65 & up living alone	Population 65 years and over: In households; In nonfamily households; Male householder; Living alone
Male HS Degree	Population 25 years and over: Male; High school graduate (includes equivalency)
Male no HS Degree	Population 25 years and over: Male; Educational attainment; below high school
MFI 1999	Households: Median Family income in 1989 (Dollars)
MHI 1999	Households: Median household income in 1989 (Dollars)
NDBI	Normalized Difference Built-up Index value within boundary from Landsat 5TM image acquired July 1, 1995
NDVI	Normalized Difference Vegetation Index value within boundary from Landsat 5TM image acquired July 1, 1995
Other Race	Total population: Some other race alone
PCI 1999	Households: Per Capita Income in 1989 (Dollars)
Pop 5 & under living in Poverty	Population for whom poverty status is determined: Income in 1989 below poverty level; 5 years and under
Pop 65 & up in Group Living	Population 65 years and over: In group quarters; communal living
Pop 65 & up living in Poverty	Population for whom poverty status is determined: Income in 1989 below poverty level; 65 years and over
Total Pop	Total population: Total
White pop	Total population: White alone

Table 1: Vulnerable Variable Definitions

A few studies identified race as a significant contributing factor to vulnerability (Davis 1997, Schwartz 2005, Whitman et al. 1997). Cutter et al. (2003), however, reported results which put race in the sixth or later factor loading in their statistical analysis. Their results could suggest race, or ethnicity itself, does not significantly contribute to vulnerability, but is correlated with other influential variables (Schwartz 2005). Race was included in this study for comparative purposes amongst the previous studies, and labeled according to the census definitions. Race variables included: White, Black, Asian, American Indian and Alaska Native, Native Hawaiian or Pacific Islander, Hispanic, and an "other race" category for any ethnicity not included in the census definitions.

Satellite Imagery

Physical environment characteristics were quantified through Landsat 5 TM imagery acquired on July 1st, 1995. This image was chosen because it provided the most complete and unobstructed view, with respect to cloud cover, of Chicago in relation to the EHE. The TM image was chosen over a Landsat 7 ETM+ image because, as previously stated, the TM had a better unobstructed view during the time period that was required. The Landsat TM image from July 1st is not during the EHE, but is from the same time period, so it can be considered to represent the thermal impact proportional to what occurred during the heat wave even if the magnitudes may be slightly off (Johnson 2009). It was therefore assumed the image would accurately depict the UHI and environmental variability across the urban landscape which would have occurred during the actual heat wave.

Landsat 5 TM data consists of seven bands, which collect data from the visible to mid-IR electromagnetic wavelengths, as well as the thermal spectrum. The Landsat TM is a passive space-borne sensor with a temporal resolution, or revisit period, of sixteen days. All wavelengths are collected at 30 m x 30 m resolution except the thermal band, which is collected at 120 meters (re-sampled to 60 m pixels by the proprietors). This resolution provided enough spatial acuity of the environment to adequately identify and measure the environmental variables required for this analysis. The imagery was utilized to calculate three environmental variables: UHI, NDVI and NDBI.

Principal Component Analysis

To better understand how the vulnerability input variables interact to create the severity of an area's vulnerability, a method of data reduction is needed. Exploratory Factor Analysis (EFA) can be used to identify the underlying constructs of variables, to identify trends among the variables and which features are more important to the overall classification of a group of features (DeCoster 2004). This type of method can be used to see which input variables are similar in their variability, and create a simpler set of factors which represents the majority of the variance and reduce the quantity of input variables, a method called data reduction. The factor analysis conducted during this experiment utilized a method known as the Principal Component Analysis (PCA). Both the EFA and the PCA methods are able to identify underlying constructs, which can account for the variability in the data, but the PCA is slightly better suited for data reduction procedures (DeCoster 2004). The PCA's data reduction method simplifies a multivariable dataset by identifying the input variables' dimensionality, or correlation amongst themselves; it than creates new factors by restructuring the data into new combined factors, which express a majority of the variance found in the original dataset. This can be accomplished by creating a multidimensional scatterplot of the variables than utilizing a rotational axis strategy to realign the graph's axis along the plotted data points to simplify cluster positions (StatSoft). Rotating the axes can be compared to the methodology used by a regression line, and is used to better understand the correlation of the variables. PCAs can be compared by the number of factors they produce; the fewer components that are needed to demonstrate the variance, the more correlated the original data is and the better model they produce. The PCA is robust enough for multidimensional modeling and was adequately able to transform this study's input variables into a matrix of components. The process for this study was conducted by the statistical program PASW (also known as SPSS) Statistics' Dimension Reduction processes.

A PCA produces as many output variables as the input dataset has, however fewer components can be used to describe the variance of the original data. Because the originals variables have been reorganized, some of the PCA components represent a larger portion of the variance than any single variable from the original dataset. The quantity of variance explained by each component is called its eigenvalue (Statsoft). According to the Kaiser criterion, any component with an eigenvalue less than one (1) does not improve the representation of the variance, since it explains less variance than any of the original input variables, and can be removed from the component list to simplify the quantity of components used in the analysis without losing much of the explained variance (Kaiser 1960, Statsoft, UCLA). Therefore any component with an eigenvalue greater than one (1), meaning it is able to represent more variance than any one (1) of the original variables, is considered to be a principal component and used for future analysis (Kaiser 1960). Therefore, a PCA with fewer components designates a more correlated dataset and demonstrates the original variables or test parameters produced a better understanding of the results (UCLA).

The PCA in this analysis was first conducted on the raw data acquired at each boundary layer. This raw data consisted of count data for all census derived variables. The environmental variables consisted of a generalized value, created by averaging the pixel values within each boundary type. To test whether the counted census data and raster data from the environmental variables had different impacts on the component loadings, a second series of PCA tests was conducted utilizing rasterized data for all variables by processing the census data through a Kernel Density Function.

A Kernel Density Function (KDF) transforms geographically spaced variables into a continuous raster or density map. This procedure transforms and normalizes data, and can reduce confounding errors caused by arbitrary political boundaries in the census data. The KDF converted the counted census data into a raster format, with a 30 m pixel output to match the resolution of environmental variables acquired by the Landsat 5 TM. The normalized variables were then aggregated to the political boundaries for statistical analysis by averaging the pixel values within each boundary as was done for the environmental variables in the first PCA.

RESULTS

Phase I – Political Boundary Analysis

The PCA output contained seven components at both the census tract and block group political boundaries, which explained 82.282 and 75.661 percent of the variance respectively. The component matrix demonstrated total population as the most significant contributor for the first component's explanation of variance at both the census tract and block group resolutions. Statistically this makes sense, as population increases the probability of observing a mortality, in a closed analysis, also increases. The results also demonstrated the importance of educational attainment and population age, particularly those 5 years old and younger at both resolutions. The census tract analysis also included age 65 and up, suggesting age is an important contributor to vulnerability. Age influencing vulnerability prediction is not surprising, as it is listed as a prevalent vulnerability indicator in many previous EHE studies (Dolney and Sheridan 2006, Semenza et al. 1999, Whitman et al. 1997). The communalities chart similarly demonstrates that total population and age variables are principal components at both resolutions and explain a significant proportion of the variance among the variables.

Extraction of environmental variables (NDVI, NDBI and temperature) from political boundaries demonstrated similar results between the census tract and block group tests. None of the environmental variables appeared to significantly improve the explanation of variance at either resolution. NDBI and NDVI appeared in the fourth component for both spatial tests. NDBI was loaded at 0.627 for census tract and 0.620 for block group in the fourth component, while NDVI was listed as -0.606 for census tract and -0.636 for block group. LST, or proximity to UHI, provided the best environmental explanation of variance as it appeared in the second component, -0.624 and 0.632 census tract and block group respectfully. This data does not offer much support for the theory of environmental factors strongly influencing vulnerability, as was predicted in this analysis, because none of them appeared in the first component loading. UHI located in the second component is a strong contributor for the identification of environmental vulnerability, but does not demonstrate the same relationship as was described in Johnson et al. (2009). The communalities suggest that the NDVI and NDBI are well represented in the common factor space. Temperature, although lower than the previous two variables, has a communality value of 0.725 for census tract and 0.726 for block group. This demonstrates that temperature is still well represented. These results, however, still suggest that specific socioeconomic variables were more explanatory than the environmental characteristics during these test parameters.

The SPSS output also provided factor loadings, which incorporates the unique values of each input variable and processes a factor score for each boundary. These factor scores were able to be mapped by utilizing the census boundary unique ID fields which were used throughout each phase of the study to maintain a constant ID. The outputs provided us a measure of vulnerability indication across the Cook County environment. The vulnerability maps for each trial and resolution can be found in the appendixes. Vulnerability maps which utilize only the first component are located in Appendix C, while those which follow the Cutter et al. (2003) methodology of utilizing the sum of all components can be found in Appendix B. Both versions of the vulnerability maps utilize a five (5) coded level of vulnerability assessment, which ranges from low to high vulnerability, and is divided into the categories by a quantile distribution of the vulnerability PCA output. The full PCA outputs are also provided in Appendix A, to complement the abbreviated tables found following each phase's analysis of results.

Total Variance of Census Tract Boundary Extraction Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.078	32.42	32.42	9.078	32.42	32.42
2	5.847	20.882	53.302	5.847	20.882	53.302
3	2.598	9.28	62.582	2.598	9.28	62.582
4	2.12	7.572	70.154	2.12	7.572	70.154
5	1.338	4.778	74.932	1.338	4.778	74.932
6	1.042	3.722	78.654	1.042	3.722	78.654
7	1.016	3.628	82.282	1.016	3.628	82.282

Extraction Method: Principal Component Analysis.

Table 2: Total variance explained by phase I Census Tract boundary

Component Matrix[a] of Census Tract Boundary Test

	Component						
	1	2	3	4	5	6	7
Total Pop	0.952	-0.091	0.118	-0.039	0.045	-0.064	0.074
Male HS Degree	0.872	0.005	0.002	0.009	-0.277	-0.146	0.058
Female HS Degree	0.868	-0.172	-0.092	0.028	-0.295	-0.121	0.046
Male 5 & under	0.842	0.237	0.255	-0.246	0.048	-0.035	0.014
Female age 5 & under	0.829	0.252	0.266	-0.272	0.057	-0.023	0.001
Male age 65 & up	0.772	-0.468	-0.17	0.181	-0.086	-0.035	0.013
Female age 65 & up	0.761	-0.438	-0.258	0.243	-0.086	0.001	-0.033
LST	-0.212	0.632	0.117	0.433	0.084	-0.206	0.175
NDBI	-0.316	0.554	0.037	0.627	0.108	-0.206	0.136
NDVI	0.317	-0.585	-0.091	-0.606	-0.153	0.202	-0.12

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Table 3: Component matrix of phase I Census Tract boundary

Communalities

	Initial	Extraction
Total Pop	1.000	.941
MHI 1999	1.000	.929
Hispanic pop	1.000	.920
MFI 1999	1.000	.908
Female age 65 & up	1.000	.905
Below Poverty	1.000	.902
Female age 5 & under	1.000	.899
NDVI	1.000	.897
Female HS Degree	1.000	.896
Other Race	1.000	.894
Male 5 & under	1.000	.894
PCI 1999	1.000	.892
White pop	1.000	.891
Male age 65 & up	1.000	.885
Hawaiian pop	1.000	.881
Black pop	1.000	.874
NDBI	1.000	.873
Male HS Degree	1.000	.861
Female age 65 & up living alone	1.000	.840
Pop 5 & under living in Poverty	1.000	.835
Female no HS Degree	1.000	.788
Pop 65 & up living in Poverty	1.000	.755
Male no HS Degree	1.000	.730
Male age 65 & up living alone	1.000	.727
LST	1.000	.725
Pop 65 & up in Group Living	1.000	.608
American Indian pop	1.000	.455
Asian pop	1.000	.435

Table 4: Communality list for phase I Census Tract boundary

Total Variance Explained of Block Group

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.459	26.641	26.641	7.459	26.641	26.641
2	5.291	18.896	45.537	5.291	18.896	45.537
3	2.675	9.552	55.089	2.675	9.552	55.089
4	2.223	7.939	63.028	2.223	7.939	63.028
5	1.351	4.826	67.854	1.351	4.826	67.854
6	1.178	4.208	72.062	1.178	4.208	72.062
7	1.008	3.599	75.661	1.008	3.599	75.661

Extraction Method: Principal Component Analysis.

Table 5: Total variance explained by phase I Block Group boundary

Component Matrix[a] of Block Group Political Boundaries

	Component						
	1	2	3	4	5	6	7
Total Pop	0.877	0.272	0.207	0.01	0.048	-0.171	-0.001
Male HS Degree	0.768	0.163	0.075	-0.038	-0.333	-0.231	-0.023
Male 5 & under	0.754	-0.097	0.433	-0.142	0.08	-0.053	-0.006
Female HS Degree	0.752	0.355	-0.06	-0.045	-0.316	-0.173	0.011
Female age 5 & under	0.748	-0.107	0.434	-0.161	0.103	-0.032	0.014
LST	0.114	-0.624	-0.141	0.497	0.088	-0.221	-0.018
NDVI	-0.11	0.597	0.241	-0.636	-0.159	0.227	0.025
NDBI	0.131	-0.542	-0.28	0.62	0.165	-0.299	-0.019

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Table 6: Component matrix of phase I Block Group boundary

Communalities

	Initial	Extraction
Hispanic pop	1.000	.921
Total Pop	1.000	.918
Hawaiian pop	1.000	.911
NDVI	1.000	.908
MFI 1999	1.000	.896
NDBI	1.000	.890
Other Race	1.000	.890
MHI 1999	1.000	.889
Below Poverty	1.000	.886
Female age 65 & up	1.000	.863
White pop	1.000	.860
PCI 1999	1.000	.852
Female HS Degree	1.000	.828
Female age 65 & up living alone	1.000	.815
Male age 65 & up	1.000	.814
Black pop	1.000	.811
Pop 5 & under living in Poverty	1.000	.801
Female age 5 & under	1.000	.797
Male 5 & under	1.000	.795
Male HS Degree	1.000	.787
LST	1.000	.726
Pop 65 & up living in Poverty	1.000	.700
Male age 65 & up living alone	1.000	.666
Female no HS Degree	1.000	.547
Male no HS Degree	1.000	.518
Asian pop	1.000	.385
American Indian pop	1.000	.269
Pop 65 & up in Group Living	1.000	.240

Table 7: Communality list for phase I Block Group boundary

Phase II – NLCD Residential Boundary Analysis

Extraction of environmental features based on residential areas produced a PCA analysis with seven components at the census tract and eight components at the block group resolution. The census tract analysis again produced a better explanation of the variability between the two, with 80.480 percent of the variance explained. The block group explained 77.098 percent of the variance. The phase II census tract spatial resolution test explained less of the variance than the census tract trial from phase I. The block group, however, provided approximately 1.5 percent better explanation of variance in phase II than the phase I block group trial. Both spatial units listed total population as the variable most responsible for the total variance explained. Educational attainment and age, specifically those 5 years old and younger, were also factors responsible for component one at both resolutions. These are the same variables outlined in phase I and are well represented in the communalities chart in both resolutions. It is noteworthy that the block group resolution explained a larger percent of the variance than it did in phase I, but has an additional component. This is an interesting situation because it suggests variables were not as strongly correlated during this phase, thus requiring another component, but still provided a larger percent explanation of variance than phase I. This could be causd by the resolution of the environmental variables, which saw a drastic decline in significance between phase I and II.

Extraction of environmental variables at the residential boundaries produced very meager results. Temperature was listed in component six for the census tract level and components seven and eight for the block group level of analysis. The NDVI and NDBI were listed in component four at each resolution. These results were mirrored in the communalities chart for census tract where UHI was listed lower. The block group resolution, however, had high values for all environmental variables in the communalities, with proximity to UHI having the largest value. This suggests the environmental variables are strongly linked to changes in vulnerability but could be encountering an obstacle in our methods. The meager component matrix loading for UHI in this phase, compared to phase I political boundaries, could be the result of reduced pixel averaging for raster vulnerability variables. The satellite pixel resolution is relatively large, 30 m x 30 m (120 m acquisition/60 m output for thermal). The decreased area within residential boundaries could have influenced the results. The residential features are also not represented by a single polygon as the political boundaries from phase I are continuous features. The scattered smaller areas could further influence the raster derived environmental variable for the same reason as previously mentioned, the calculation difficulties between pixel size and boundary areas. The results could also have been influenced by the removal of high density residential and vegetation areas. NLCD areas classified as low to medium residential areas were used to create the boundary layer. Removing areas of high residential density (commercial/residential mixed land use), forest, wetland, and waterways could confound the results. This is particularly significant to note because the areas removed from the analysis would be the most extreme contributors for all three environmental variables. These areas would have been incorporated into phase I, political boundary, analysis and could suggest why they were under represented during phase II results. As the analysis continued, the prior theory was supported, that boundary size impacted the results rather than nonresidential features, as will be demonstrated through the remaining results. These initial residential test results were not very promising for environmental variable influence on vulnerability in this study. If the KDF iteration had not proven more beneficial, the utilization of residential NLCD classification boundaries would only have been useful for cities with more urban spread and less mixed building use, such as Indianapolis, IN.

Total Variance of Census Tract Residential Test Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.996	32.128	32.128	8.996	32.128	32.128
2	5.457	19.489	51.617	5.457	19.489	51.617
3	2.59	9.25	60.867	2.59	9.25	60.867
4	2.06	7.358	68.225	2.06	7.358	68.225
5	1.369	4.888	73.112	1.369	4.888	73.112
6	1.038	3.707	76.82	1.038	3.707	76.82
7	1.025	3.66	80.48	1.025	3.66	80.48

Extraction Method: Principal Component Analysis.

Table 8: Total variance explained by phase II Census Tract boundary

Component Matrix[a] of Census Tract Residential Test

	Component						
	1	2	3	4	5	6	7
Total Pop	0.946	0.14	0.113	-0.044	0.048	0.029	0.022
Male HS Degree	0.872	0.046	-0.004	-0.031	-0.267	0.133	-0.013
Female HS Degree	0.859	0.221	-0.103	-0.04	-0.288	0.112	-0.009
Male 5 & under	0.851	-0.197	0.283	-0.22	0.053	-0.009	-0.011
Female age 5 & under	0.839	-0.214	0.298	-0.242	0.063	-0.022	-0.015
NDVI	0.222	0.533	0	-0.681	-0.146	-0.087	0.027
NDBI	-0.228	-0.505	-0.06	0.681	0.15	0.242	0.026
LST	0.079	-0.027	0.028	0.035	0.262	0.723	0.218

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Table 9: Component matrix of phase II Census Tract boundary

Communalities

	Initial	Extraction
Total Pop	1.000	.932
MHI 1999	1.000	.917
Hispanic pop	1.000	.908
Female age 65 & up	1.000	.908
Below Poverty	1.000	.903
Female age 5 & under	1.000	.902
Male 5 & under	1.000	.896
Female HS Degree	1.000	.895
Male age 65 & up	1.000	.890
MFI 1999	1.000	.889
White pop	1.000	.889
Hawaiian pop	1.000	.887
Other Race	1.000	.879
NDBI	1.000	.856
Male HS Degree	1.000	.852
Black pop	1.000	.848
PCI 1999	1.000	.847
Female age 65 & up living alone	1.000	.834
Pop 5 & under living in Poverty	1.000	.833
NDVI	1.000	.827
Female no HS Degree	1.000	.767
Pop 65 & up living in Poverty	1.000	.742
Male age 65 & up living alone	1.000	.730
Male no HS Degree	1.000	.706
LST	1.000	.647
Pop 65 & up in Group Living	1.000	.466
American Indian pop	1.000	.452
Asian pop	1.000	.431

Table 10: Communality list for phase II Census Tract boundary

Total Variance of Block Group Residential Test Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.469	26.675	26.675	7.469	26.675	26.675
2	4.953	17.691	44.366	4.953	17.691	44.366
3	2.672	9.542	53.909	2.672	9.542	53.909
4	2.006	7.163	61.072	2.006	7.163	61.072
5	1.349	4.816	65.888	1.349	4.816	65.888
6	1.125	4.019	69.907	1.125	4.019	69.907
7	1.009	3.603	73.51	1.009	3.603	73.51
8	1.005	3.588	77.098	1.005	3.588	77.098

Extraction Method: Principal Component Analysis.

Table 11: Total variance explained by phase II Block Group boundary

Component Matrix[a] of Block Group Residential Test

	Component							
	1	2	3	4	5	6	7	8
Total Pop	0.874	0.273	0.219	0.054	0.029	-0.162	-0.02	-0.036
Male HS Degree	0.765	0.163	0.08	0.079	-0.363	-0.164	0.015	-0.017
Male 5 & under	0.751	-0.117	0.423	0.19	0.065	-0.024	-0.016	-0.027
Female HS Degree	0.749	0.361	-0.049	0.096	-0.345	-0.096	-0.013	0.008
Female age 5 & under	0.744	-0.129	0.422	0.208	0.089	-0.002	-0.03	-0.009
NDVI	-0.181	0.495	0.195	0.673	-0.168	0.308	0.043	0.119
NDBI	0.206	-0.454	-0.236	-0.641	0.166	-0.399	0.054	0.001
LST	0.096	-0.033	0.017	-0.019	0.032	-0.145	0.648	0.732

Extraction Method: Principal Component Analysis.

a. 8 components extracted.

Table 12: Component matrix of phase II Block Group boundary

Communalities

	Initial	Extraction
LST	1.000	.989
Hispanic pop	1.000	.922
Total Pop	1.000	.919
Hawaiian pop	1.000	.918
NDVI	1.000	.908
NDBI	1.000	.906
MFI 1999	1.000	.903
MHI 1999	1.000	.894
Other Race	1.000	.892
Below Poverty	1.000	.888
Female age 65 & up	1.000	.871
White pop	1.000	.862
PCI 1999	1.000	.856
Female HS Degree	1.000	.831
Male age 65 & up	1.000	.820
Female age 65 & up living alone	1.000	.813
Black pop	1.000	.809
Pop 5 & under living in Poverty	1.000	.801
Female age 5 & under	1.000	.801
Male 5 & under	1.000	.798
Male HS Degree	1.000	.784
Pop 65 & up living in Poverty	1.000	.694
Male age 65 & up living alone	1.000	.662
Female no HS Degree	1.000	.542
Male no HS Degree	1.000	.514
Asian pop	1.000	.454
Pop 65 & up in Group Living	1.000	.271
American Indian pop	1.000	.266

Table 13: Communality list for phase II Block Group boundary

Phase III – KDF Analysis within Political Boundaries

Extraction of all variables, from raster form, within political boundaries produced PCA outputs with five components at the census tract and four components at the block group level of analysis. The outputs explained 87.409 percent of the variance at the census tract resolution, and 83.225 percent of the variance at the block group resolution. This is noteworthy because the smaller spatial resolution, block group, has one fewer component, suggesting its variables have a stronger correlation amongst themselves, and because they are documented indicators of vulnerability their factor scores will also strongly correlate to vulnerability. In fact, this block group boundary layer has the least amount of components amongst all resolutions and trials. This suggests spatial resolution is important for variable testing and should be considered in future studies. The census tract resolution also had its lowest quantity of components, at five, when a KDF is applied to the variables in phase III and phase IV, suggesting the KDF step helps improve the correlation amongst the variables. Particularly since the KDF trials have fewer components throughout trials compared to the non-KDF. This phase's census tract has the largest explanation of variance amongst all test iterations and resolutions.

Total population is again the best contributor to the first component at both spatial resolutions. Other variables containing strong loadings in component one include: level of education attainment, and age 5 and under. The block group analysis has additional variables with strong loadings in the first component, including: age 65 and older, social isolation (age 65 and up living alone), and financial indicators. This is the first time these variables have been introduced to such an influential extent in the analysis. The latter two appear this influential only one other time, in the block group analysis of phase IV.

This again suggests resolution and KDF both play an important role in modeling vulnerability in urban environments. The communalities chart demonstrates that total population and age were again well represented by the principal components at both resolutions, the block group resolution also contain high loadings for financial variables. The KDF analysis increased the factor loading in component one for most of the variables; particularly for the block group resolution, which contained approximately twice the number of variables contributing to component one than the census tract. This suggests that the KDF computation process may have reduced the dimensionality of the variables and has significantly improved the results, particularly when considering spatial resolution for acquiring data.

Proximity to UHI was the most contributing environmental variable at both resolutions. It was listed in the first component with loading values of 0.729 and 0.681, census tract and block group respectively. The census tract NDBI variable is split between the first, fourth, and fifth components with 0.531, -0.527, and -0.599 respectfully. The NDVI was split between the first and fifth components with respective values of -0.601 and 0.552 within the census tract. The block group analysis put the NDBI in the first and third components with 0.505 and -0.794 respectfully, while NDVI was similarly split with values of -0.604 and 0.728 respectfully. This phase represents the best impact environmental variables made amongst all trials. The communalities chart similarly demonstrates the environmental variable's strong explanation of variance among the variables. The LST is the weakest community strength of the three environmental variables, which supports the theory on needing improved resolution data, but is still considered to have a high value for communalities. This may suggest that utilizing a KDF may have removed some discrepancy between counted census data and the averaged environmental variables (acquired through the indexed remotely sensed raster data), and accounted for confounding errors created through using political boundaries, which are environmentally arbitrary, found in the previous two phases.

Total Variance of KDF Variables at the Census Tract Boundary Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.662	48.793	48.793	13.662	48.793	48.793
2	4.428	15.814	64.607	4.428	15.814	64.607
3	2.972	10.615	75.222	2.972	10.615	75.222
4	1.971	7.04	82.262	1.971	7.04	82.262
5	1.441	5.146	87.409	1.441	5.146	87.409

Extraction Method: Principal Component Analysis.

Table 14: Total variance explained by phase III Census Tract boundary

Component Matrix[a] for KDF Variables at the Census Tract Boundary

	Component				
	1	2	3	4	5
Total Pop	0.959	0.114	0.12	0.072	0.135
Male no HS Degree	0.902	-0.34	-0.074	0.059	0.014
Female age 5 & under	0.889	-0.395	0.075	-0.013	0.128
Male 5 & under	0.884	-0.406	0.088	0.01	0.125
Male HS Degree	0.869	-0.225	-0.004	0.273	-0.126
Female no HS Degree	0.86	-0.32	-0.329	-0.009	0.055
LST	0.729	-0.071	0.021	-0.308	-0.358
NDVI	-0.601	-0.119	-0.076	0.484	0.552
NDBI	0.531	0.096	-0.011	-0.527	-0.599

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Table 15: Component matrix of phase III Census Tract boundary

Communalities

	Initial	Extraction
Total Pop	1.000	.971
PCI 1999	1.000	.970
Male 5 & under	1.000	.970
Female age 5 & under	1.000	.968
MFI 1999	1.000	.966
Hispanic pop	1.000	.959
Female no HS Degree	1.000	.953
Female age 65 & up	1.000	.951
Other Race	1.000	.941
MHI 1999	1.000	.940
Male no HS Degree	1.000	.939
Black pop	1.000	.939
White pop	1.000	.937
Below Poverty	1.000	.931
NDBI	1.000	.928
NDVI	1.000	.920
Male age 65 & up	1.000	.920
Pop 5 & under living in Poverty	1.000	.912
Male HS Degree	1.000	.896
Female age 65 & up living alone	1.000	.894
Female HS Degree	1.000	.875
American Indian pop	1.000	.873
Male age 65 & up living alone	1.000	.859
Pop 65 & up living in Poverty	1.000	.846
LST	1.000	.761
Hawaiian pop	1.000	.547
Asian pop	1.000	.475
Pop 65 & up in Group Living	1.000	.434

Table 16: Communalities list for phase III Census Tract boundary

Total Variance of KDF Variables Extracted from Block Group Boundaries Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.85	63.748	63.748	17.85	63.748	63.748
2	2.445	8.733	72.482	2.445	8.733	72.482
3	1.637	5.846	78.328	1.637	5.846	78.328
4	1.371	4.898	83.225	1.371	4.898	83.225

Extraction Method: Principal Component Analysis.

Table 17: Total variance explained by phase III Block Group boundary

Component Matrix[a] of KDF Variables from Block Group Boundaries

	Component			
	1	2	3	4
Total Pop	0.982	-0.073	0.08	0.042
Female age 5 & under	0.964	0.076	0.039	-0.022
Male 5 & under	0.962	0.072	0.033	-0.011
Male HS Degree	0.947	-0.116	0.022	-0.029
Female no HS Degree	0.935	0.085	0.021	-0.223
Male no HS Degree	0.931	0.156	0.03	-0.109
Female HS Degree	0.924	-0.249	0.02	-0.066
MFI 1999	0.912	-0.207	0.035	0.056
Male age 65 & up	0.912	-0.352	0.035	-0.043
MHI 1999	0.91	-0.199	0.023	0.036
Female age 65 & up	0.908	-0.364	0.044	-0.051
PCI 1999	0.893	-0.192	0.062	0.088
Female age 65 & up living alone	0.874	-0.36	0.087	-0.015
Male age 65 & up living alone	0.868	-0.198	0.115	-0.086
White pop	0.868	-0.312	0.115	0.295
LST	0.681	0.085	-0.512	0.099
NDBI	0.505	0.048	-0.794	0.201
NDVI	-0.604	-0.017	0.728	-0.152

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Table 18: Component matrix of phase III Block Group boundary

Communalities

	Initial	Extraction
Total Pop	1.000	.978
Female age 65 & up	1.000	.962
Male age 65 & up	1.000	.958
White pop	1.000	.951
Female age 5 & under	1.000	.938
Hispanic pop	1.000	.936
Other Race	1.000	.936
Female no HS Degree	1.000	.932
Male 5 & under	1.000	.931
NDBI	1.000	.928
Female HS Degree	1.000	.921
NDVI	1.000	.919
Male HS Degree	1.000	.911
Pop 5 & under living in Poverty	1.000	.906
Black pop	1.000	.905
Below Poverty	1.000	.904
Male no HS Degree	1.000	.904
Female age 65 & up living alone	1.000	.900
MFI 1999	1.000	.879
MHI 1999	1.000	.870
PCI 1999	1.000	.845
Male age 65 & up living alone	1.000	.813
LST	1.000	.743
Pop 65 & up living in Poverty	1.000	.741
American Indian pop	1.000	.692
Asian pop	1.000	.464
Hawaiian pop	1.000	.316
Pop 65 & up in Group Living	1.000	.219

Table 19: Communalities list for phase III Block Group boundary

Phase IV – KDF Analysis within NLCD Residential Boundaries

Variables extracted by NLCD residential boundaries, after converting all vulnerability variables to a raster format, produced PCA outputs with five components for both the census tract and block group analysis. The percent of variance explained is very similar between the two spatial resolutions. The census tract analysis explained 85.147 percent of the variance and block group explained 84.356 percent. This iteration has the smallest difference between the two spatial resolutions, the gap being only 0.791 percent. The percentage of census tract variance explained during this trial is the second most predictive amongst all phases and spatial resolutions. The block group explanation of variance is the highest amongst all block group trials. This suggests there is a relationship between boundary size and acquisition size of the data, and smaller units of data can improve predictability. Explanation of variance decreased between phase III and IV for the census tract resolution, by about two percent. The block group resolution, however demonstrated an increase in explanation of variance between phase III and IV. This suggests that improved spatial identification and acquisition of data is important to consider for future studies.

Both spatial resolutions again listed total population as the best contributor for the first component. Other variables responsible for the first component, at either resolution include: age, educational attainment, and economic status. The communalities charts identify the variables with the highest correlation to the other variables, include total population and age. The census tract resolution also had financial variables with higher communality values for the first time. It is interesting to note that there was an increase of variables with strong factor loadings in the first component for both phases which used

KDF, phases III and IV, particularly for the block group resolution. The block group resolutions in phase III and IV had much stronger variable loadings to component one than at the census tract trials.

Environmental variables extracted by residential features were not as advantageous in this phase as they were in phase III. NDVI was split between the first and fifth component at the census tract level, -0.686 and 0.573 respectively. At the block group, NDVI was split between the first and fourth components, -0.617 and 0.575 respectively. The NDBI was listed in the first and fifth component at the census tract resolution, 0.582 and -0.670 respectfully. The block group listed NDBI in the first and fourth components with 0.523 and -0.643. Temperature produced very meager results in this trial, and appeared to have almost no impact on the census tract level as its highest value was -0.188 in the fifth component. The block group resolution similarly had temperature's highest value in the fifth component, but at a more notable value of 0.880. Both resolutions in this phase depict temperature as one of the least predictive variables for vulnerability, closely followed by NDBI. These results are supported by the communalities list, which lists temperature as one of the lowest values at both resolutions. The communalities list did, however, list NDVI as one of the highest valued for the block group analysis, suggesting it was highly correlated with the other variables.

These environmental results are drastically different from the phase III (KDF political boundary analysis). These results are also very contradicting of previous studies, and could be an indicator of problems arising from the spatial resolution of raster variables, particularly the 120 m thermal data (Harlan et al. 2006, Johnson et al. 2009). They could also suggest how influential neighboring environmental features are on the impact of residential vulnerability. This phase removed areas not classified as residential by the NLCD. That could impact the environmental variables' influence of extreme loading areas found outside residential boundaries on the analysis. As with phase II (census count data within residential boundaries) environmental variables did not contribute to the analysis as well as was expected. This suggests improved resolution environmental datasets need to be tested as the smaller and disconnected boundaries of the residential boundary layer may be reducing the impact of environmental variables, particularly for the large resolution LST data.

Total Variance of KDF Variables Extracted from Census Tract Residential Boundaries Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.258	47.349	47.349	13.258	47.349	47.349
2	4.541	16.218	63.567	4.541	16.218	63.567
3	2.981	10.646	74.213	2.981	10.646	74.213
4	1.874	6.693	80.906	1.874	6.693	80.906
5	1.188	4.241	85.147	1.188	4.241	85.147

Extraction Method: Principal Component Analysis.

Table 20: Total variance explained by phase IV Census Tract boundary

Component Matrix[a] of KDF Variables from Census Tract Residential Boundaries

	Component				
	1	2	3	4	5
Total Pop	0.963	0.096	0.13	0.021	0.139
Male no HS Degree	0.894	-0.36	-0.075	0.047	0.017
Female age 5 & under	0.879	-0.419	0.078	-0.067	0.101
Male 5 & under	0.874	-0.431	0.091	-0.044	0.102
Male HS Degree	0.859	-0.245	0.001	0.305	-0.01
Female no HS Degree	0.852	-0.335	-0.332	-0.022	0.053
NDVI	-0.686	-0.192	-0.036	0.254	0.573
NDBI	0.582	0.176	-0.072	-0.336	-0.67
LST	0.153	-0.017	-0.003	-0.099	-0.188

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Table 21: Component matrix of phase IV Census Tract boundary

Communalities

	Initial	Extraction
Total Pop	1.000	.972
Male 5 & under	1.000	.970
Female age 5 & under	1.000	.968
PCI 1999	1.000	.968
MFI 1999	1.000	.965
Hispanic pop	1.000	.962
Female age 65 & up	1.000	.953
Female no HS Degree	1.000	.951
Other Race	1.000	.944
Black pop	1.000	.944
White pop	1.000	.939
MHI 1999	1.000	.937
Male no HS Degree	1.000	.937
NDBI	1.000	.937
Below Poverty	1.000	.935
Male age 65 & up	1.000	.921
Pop 5 & under living in Poverty	1.000	.917
NDVI	1.000	.901
Female age 65 & up living alone	1.000	.895
Male HS Degree	1.000	.890
American Indian pop	1.000	.874
Female HS Degree	1.000	.871
Male age 65 & up living alone	1.000	.865
Pop 65 & up living in Poverty	1.000	.851
Hawaiian pop	1.000	.533
Asian pop	1.000	.506
Pop 65 & up in Group Living	1.000	.466
LST	1.000	.069

Table 22: Communalities list for phase IV Census Tract boundary

Total Variance of KDF Variables at the Block Group Residential Trial Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.424	62.228	62.228	17.424	62.228	62.228
2	2.467	8.811	71.039	2.467	8.811	71.039
3	1.449	5.175	76.214	1.449	5.175	76.214
4	1.279	4.567	80.781	1.279	4.567	80.781
5	1.001	3.574	84.356	1.001	3.574	84.356

Extraction Method: Principal Component Analysis.

Table 23: Total variance explained by phase IV Block Group boundary

Component Matrix[a] of KDF Block Group Residential Trial

	Component				
	1	2	3	4	5
Total Pop	0.984	-0.066	0.074	-0.003	0.006
Female age 5 & under	0.965	0.083	-0.011	0	0.039
Male 5 & under	0.963	0.08	-0.008	-0.01	0.035
Male HS Degree	0.947	-0.11	-0.012	0.017	0.034
Female no HS Degree	0.935	0.094	-0.143	0.168	-0.032
Male no HS Degree	0.93	0.166	-0.06	0.085	-0.025
Female HS Degree	0.925	-0.245	-0.034	0.048	0.034
Male age 65 & up	0.913	-0.351	0.001	0.05	0.013
MFI 1999	0.912	-0.203	0.055	-0.044	0.091
MHI 1999	0.91	-0.197	0.028	-0.043	0.105
Female age 65 & up	0.91	-0.361	0.005	0.068	0.003
PCI 1999	0.893	-0.187	0.099	-0.045	0.074
Female age 65 & up living alone	0.875	-0.354	0.07	0.085	-0.029
White pop	0.869	-0.306	0.275	-0.163	0.018
Male age 65 & up living alone	0.867	-0.19	0.051	0.172	-0.078
NDVI	-0.617	0.039	0.472	0.575	0.074
NDBI	0.523	-0.006	-0.483	-0.643	0.107
LST	0.143	0.026	0.07	0.113	0.88

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Table 24: Component matrix of phase IV Block Group boundary

Communalities

	Initial	Extraction
Total Pop	1.000	.978
Female age 65 & up	1.000	.962
Male age 65 & up	1.000	.959
White pop	1.000	.951
NDVI	1.000	.942
Female age 5 & under	1.000	.941
Hispanic pop	1.000	.937
Other Race	1.000	.937
Male 5 & under	1.000	.935
NDBI	1.000	.933
Female no HS Degree	1.000	.933
Female HS Degree	1.000	.921
Below Poverty	1.000	.919
Pop 5 & under living in Poverty	1.000	.912
Male HS Degree	1.000	.911
Male no HS Degree	1.000	.904
Female age 65 & up living alone	1.000	.903
Black pop	1.000	.902
MFI 1999	1.000	.887
MHI 1999	1.000	.880
PCI 1999	1.000	.850
Male age 65 & up living alone	1.000	.827
LST	1.000	.813
Pop 65 & up living in Poverty	1.000	.770
American Indian pop	1.000	.694
Asian pop	1.000	.491
Hawaiian pop	1.000	.335
Pop 65 & up in Group Living	1.000	.294

Table 25: Communalities list for phase IV Block Group boundary

Phase V – Residential Building Code Zones

The analysis utilizing building code ID's to differentiate areas of residential use could not be utilized in this study because of multiple problems. The first problem was the data available through the city of Chicago's building and zoning department did not cover the necessary area of the study. The available data only covered the Chicago city limits, rather than Cook County, which was not enough area for the analysis, as can be seen in Figure 4 and Figure 7. Without the full county data, the test could not be adequately compared to the other phases, contain all documented heat mortalities, or compensate for edge effect errors. Secondly, the Chicago building zone codes are written in such a way that the majority of commercial or business zones allow for the construction of residential living space above ground level businesses. This stipulation allowed for the removal of only the downtown central business district and industrial facilities outside the city. Utilizing the remaining codes, which allow for residential living, would remove very little area from the political boundaries. The building code data would not improve spatial resolution analysis much from the census political boundaries. Therefore, due to the multiple dilemmas, and few statistical gains, this analysis was removed from the experiment.

CONCLUSIONS

The analysis and identification of vulnerability was appropriately accomplished for Cook County, IL. The analysis was able to explain the variability between vulnerable places, using the input vulnerability variables, by at least 75.661 percent across all test iterations. The highest explanation of variance occurred in phase III, when KDF vulnerability variables were extracted through the census tract political boundaries. This iteration contained a PCA output with five components and explained 87.409 percent of the variance. The second highest explanation of variance was 85.147 percent during the phase IV KDF census tract residential boundary trial, which also had five components. Phases III and IV at the block group resolution explained 83.225 and 84.356 percent, respectfully, of the variance amongst the vulnerability variables used in this analysis. Those results were also able to demonstrate the block group trials were able to accurately account for the variability between the vulnerable variables. The block group resolution of phase IV had five components, suggesting its variables were as correlated together as the before mentioned phase III and IV census tract trials. The phase III block group trial, however, contained a PCA output with four components, which was the lowest quantity amongst all studies and suggests that test had the highest correlation among all trials.

The results demonstrate the parameters of the study, with respect to both spatial resolution and KDF application, influenced the results and has provided an idea of how vulnerability can be defined. The quantity of components in the census tract trials were consistent whether KDF was utilized or not. The block group, however, had a different number of components for each phase of the study. This suggests that the block group resolution is impacted more by the parameters of the study and could suggest the increased spatial resolution it provides will be more influential for improving vulnerability analysis during future studies.

The changing parameters between phases and spatial resolutions also suggest the importance of specific variables, which consistently appeared in the first component loadings. These variables included: total population, educational attainment, and age (particularly those 5 years of age and younger). These findings are consistent with many previous research projects (Cutter et al. 2003, Dolney and Sheridan 2006, Johnson and Wilson 2009, Johnson et al. 2009, Naughton et al. 2002, Whitman et al. 1997). Total population appeared as the most important contributor for component one in every test. This suggests that population is a significant vulnerability variable. It could also simply be a statistical probability; as the population increases within a boundary, the probability of someone being vulnerable, or of a mortality occurring, in that area also increases. That should not minimize the utilization of total population, however, because this study did provide some conditions which addressed that issue. Firstly, the use of political boundaries helped improve the population consistency between census boundaries, as they are designed to be proportional amongst themselves in regards to population size. The KDF process similarly utilized a population density process which similarly helped correct for disparities in population. Therefore, the results should be considered highly realistic and strongly suggests that total population should be included in future studies. Future studies, however, could expand the analysis to compare total population against additional population density variables to further define the impact population makes on vulnerability and definitively prove the results were not due to simple probabilities.

The component loadings indicated environmental variables (NDVI, NDBI, and temperature) contributed well to the analysis during phase III, the KDF within political boundaries trial. This could be the result of mixed pixels from the remotely sensed data, resolution problems, or because environmental index variables were compared to census count variables during non-KDF trials. When utilizing the KDF process, all variables were transformed into raster variables and became more comparable because they were all index variables. Not only did the variables become more comparable, because they were in the same index units, the results also demonstrated the benefits of the KDF process. The results saw an increase in correlation amongst the variables when a KDF was utilized; fewer components were needed, making the analysis better. KDF should be considered a crucial part of future studies and vulnerability warnings.

Previous research projects, such as those conducted by Johnson et al. (2009) and Cutter et al. (2003) suggested this analysis would demonstrate the importance of environmental variables in predicting EHE mortalities. There is a consensus from many worldwide management programs that acknowledge the link between the environment and environmental safety, even the World Bank "provides data on the links between environmental conditions and human welfare (Cutter et al. 2003, 245)." Their studies suggest environmental variables should have been strongly correlated to vulnerability variables in each phase, but these results did not demonstrate the interaction being as strong as expected. The results do, however, suggest that environmental variables should be retested using different parameters, because the resolution and processes greatly impacted the individual phases' results. In other words, the component loadings for environmental variables changed significantly between trials. They appeared in the first component during multiple iterations, which demonstrates they are correlated with the other variables. Their “inconsistent” correlation between phases in this study suggests the environmental variables were strongly influenced by test procedures and methods, much more so than the socioeconomic variables used. For that reason, environmental variables should be included in future studies; they may be more important in understanding vulnerability than this study was able to document.

Another expected outcome of this study was more spatially specific acquisition of data and variables would improve the analysis. The results, however, do not specify a resolution as being better. The results suggest the larger census tract boundary was the better spatial unit for an explanation of variance in this experiment. Phase III, political boundary KDF analysis, had the highest overall explanation of variance (87.409 percent) at the census tract resolution, but also had one more component than the block group boundary from the same phase, for a total of five. The census tract provided a better explanation of variance for that trial, but demonstrated the block group was more correlated to the documented vulnerability variables because the block group resolution had one less component. This suggests the smaller spatial boundaries, block group and residential, are better spatial units to use for vulnerability prediction, but were too small to isolate trends derived from large spatial resolution data in this study. This is particularly noticeable when the NLCD residential boundaries were used. For both the KDF and non-KDF trials, the residential zones increased the variance explained by the block group resolution, while the census tract became less explanatory between the political to residential boundary trials. This could suggest there was a contributing relationship between using smaller residential boundaries and smaller political boundaries, which the larger census tract boundary could not utilize.

The larger explanation of variance by the census tract resolution can probably be attributed to the fact that some raster pixels were similar in size or larger than the smaller block group boundaries, and could therefore provide less estimation of trend. Improved spatial acquisition of environmental variables, such as through the utilization of improved resolution imagery and KDF variables, should improve the analysis and remove errors associated with pixel size complications. The resolutions utilized for this study were able to accurately depict vulnerability for Cook County, but improved resolution could provide more accurate analysis and lead to even more spatially specific warning systems. More spatial resolution tests should be included in future studies to improve the accuracy assessment of the vulnerability trend from this study and improve vulnerability analysis.

Although, as just stated, improved resolution is superior, this analysis demonstrated this level of analysis could be conducted at either the census tract or block group resolution to get predictive vulnerability data. Both resolutions provided strong results and the variance explained at either resolution was always similar. The average difference between the two political boundaries explanation of variance was only 3.75 percent; the largest difference was only 6.621 percent during phase I, which used political boundaries without the KDF. The range of variance explained by the census tract boundaries was 6.929 percent, block group was 8.695 percent. Since the block group trials experienced a larger range, it suggest those studies were more impacted by the changing test parameters between phases. This should be tested in future research by improving the spatial resolution of vulnerability data, including the remotely sensed environmental variables and socioeconomic KDF variables. For current methods though, these results suggest either could be used for predictive modeling of vulnerability and used to positively identify areas of increased vulnerability during an EHE, though the improved resolution will provide more specific and better results.

This study demonstrated some variables are less important for identifying vulnerability than has been stated in previous research. Race, for example, was only present in a higher component loading during the block group iteration of phase III and IV, which used the KDF process. Even then, only one variable, white, was recorded as being more correlated to the other variables used for vulnerability identification. This is in line with the analysis of Cutter et al. (2003), who reported race only appeared in the sixth or later factor loading of their statistical analysis. Other studies have similarly stated race disparities in heat vulnerability were minimal and could be attributed to other socioeconomic issues (O'Neill et al. 2005). Supported by those researchers, the results of this project suggest that previous studies, such as: Davis (1997), Whitman et al. (1997), Schwartz (2005), and Kalkstein and Davis (1989), misidentified race as a predictive variable for mortality. Their results were probably the result of correlation errors between race and other socioeconomic variables within their studies. The utilization of race in future studies should continue though, because a consistent set of variables needed to improve our understanding of vulnerability. These results are based on the demographics of Chicago, IL and additional research between urban areas needs to be conducted to see how vulnerability changes or remains consistent between years and urban environments.

Finances similarly did not provide as much support as previous research suggested. Financial variables, not considering educational attainment, were limited contributors to vulnerability except during phase III and IV when a KDF was applied to the analysis. The variable below poverty, in particular, did not demonstrate it was strongly correlated to the vulnerability variables during any phase, as has been suggested by Changnon et al. (2009), and Naughton et al. (2002). The financial variables which contributed more often to vulnerability prediction were measures of Medium Household Income and Per Capita Income. From these results, there is no definitive way to identify whether low or high economic values were correlated to the other vulnerability variables. Since poverty did not consistently prove influential in the analysis, no definitive statement of whether lower economic standings increase a neighborhood's risk of vulnerability or if higher economic neighborhoods were less vulnerable, as is suggested by McMichael et al. (2008), can be made. Similarly, these results cannot specify if the changes in mortality rates were due to improved warning or utilization of air conditioning in more wealthy neighborhoods. However, the background literature suggests the financial variables create an inverse relation between heat vulnerability and wealth, increased wealth decreases risk. This is also supported by the relation between finances and population density. The wealthier a neighborhood is, the increased amount of space between residents. This is most notable among larger property value's relation to increased wealth, and poverty's relation to densely built/small apartments. With the impact financial variables made, particularly during phase III and IV of this analysis, poverty and the other financial variables should be considered to be influential to an area's risk to EHE (Chander et al. 2009, Johnson et al. 2009, Naughton et al. 2002, O'Neill et al. 2005). Future studies should incorporate financial variables in analysis, and additional tests should be conducted to determine which of the variables utilized in this study are more predictive of weather vulnerability. This study demonstrated income variables are more predictive of vulnerability than poverty counts.

Educational attainment was listed as influential during every phase of this experiment, and should be considered a vital variable for predicting vulnerability. Higher educational attainment can be seen as a neighborhood's ability to understand and adapt to the hazardous conditions during an EHE, improving their probability of surviving. Education is also considered related to an individual's financial stability. Therefore educational variables should also be incorporated in future vulnerability studies.

The KDF methodology increased the explanation of variance in each trial, and improved the contribution each variable, environmental and socioeconomic, made to the component one loading. It made the input variables more correlated so there were fewer components with an eigenvalue greater than one during each phase, suggesting it improved each variable's relation to the overall variance. This suggests the KDF was successful in reducing confounding errors in the analysis, such as reducing the impact geographically arbitrary political boundaries had on the analysis, and made the environmental and socioeconomic variables into more comparable index variables. The KDF also produced a strong visible fit between mortality and mapped risk when comparing the vulnerability maps and the mortality density map found in Figure 8.

A good vulnerability predictive model will show predicted risk level increases congruent with an increase in heat related mortalities occurring in those areas as well. This positive correlation only occurred in three of the eight trials when mapping only the first component. The majority of the trials resulted in negative mortality trends or parabolic graphs, where the highest quantity of heat mortalities occurred in high and low risk areas, with the least amount occurring in medium risk areas. The three positive correlation trials, however, produced an increase from low to high mortality count, congruent with risk. The block group and census tract resolutions of the KDF within residential boundaries (phase IV), and the KDF within political boundaries at the census tract resolution (phase III) provided the positive mapped correlations. These trends can be seen in the vulnerability maps found in Appendix C. This suggests the KDF analysis provided a method for a better fit of vulnerability estimates. This is supported by the fact that phase III (KDF within political boundaries) provided the greatest explanation of variance overall in the census tract resolution, and both phase III and IV saw a decrease in the quantity of components. The KDF methodology should therefore be considered influential in the prediction of EHE vulnerability, and utilized in future studies.

The KDF process also provides more gradient risk maps than non KDF trials. As can be seen in Appendix B, of mapped vulnerability based on the summation of all component factor scores as is specified in the methods of Cutter et al (2003), KDF risk maps at both resolutions have less scatter in vulnerability prediction. Rather, the maps provide a clear trend of vulnerability rankings across the landscape. This same process can also be viewed in Appendix C with the risk mapping of component one only. This further suggests that the KDF was able to reduce the impact of arbitrary political boundaries to provide a map which demonstrates a more natural trend of risk.

This theory of more smooth risk maps producing more realistic maps is also more prone amongst the census tract resolution, rather than block group. This is probably, as previously mentioned, due to the spatial specificity of input variables being too small to isolate risk trend. The block group trials may not have been able to isolate the trend of variables across the study area, due to the larger resolution of environmental and KDF raster variables. This, however, does not suggest the block group trials are less predictable than the results demonstrate. Rather, it further suggests that incorporating finer scale resolution imagery and KDF cells could improve the block group resolutions ability to improve risk prediction. This is particularly relevant to consider when comparing the phase IV resolutions. The block group analysis was able to distinguish and identify boundaries of low risk to heat waves which were surrounded by high risk areas. The census tract resolution labeled all these areas as high risk, which in a real world application could misdirect city officials to send preventative aid to areas which do not require assistance, spreading the aid too thin across areas in need. The improved sensitivity of the block group resolution to these fluctuations could improve emergency personal planning for EHEs. As can be seen in Appendix B, the phase IV block group map better approximates the vulnerability in Chicago than its census tract counterpart because it more properly aligns with the mortality density map, Figure 8. Although the census tract documented a higher explanation of variance, the block group residential boundaries appears to better represent the vulnerability, as can be seen in Figure 9. This further demonstrates why resolution and utilization of residential areas are extremely important for future studies.

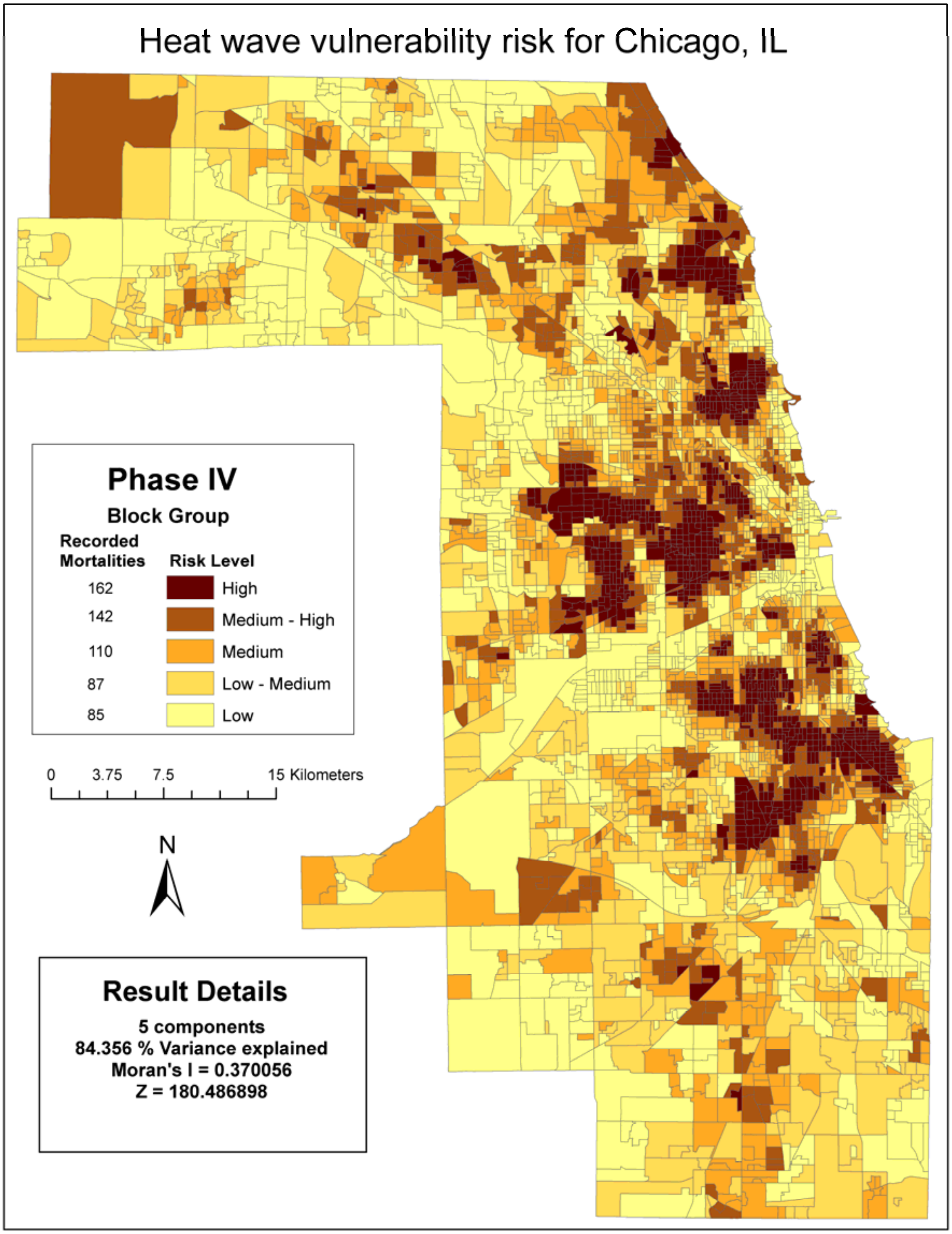


Figure 9: Predicted vulnerability of Chicago, IL

Future research should focus on expanding upon the variations of socioeconomic variables and spatial resolutions tested in this analysis. These results demonstrated many socioeconomic variables were not as predictive as previous research suggested, such as:

poverty, social isolation, or age 65 and up. This could be a result of how the variables were defined in these methods. Age and social isolation, for example, were divided into separate gendered, male and female, variables. A future study may find isolation is more statistically relevant to vulnerability if the gendered variables were combined into a single variable, all citizens age 65 and up living alone. Similarly, variables which listed salary ranges may have appeared more correlated to mortality because of the larger range. It can be difficult to statistically compare variables in a regression when one is comprised of six digits and the other two (example household income of 100,000 vs. 10 people living in poverty). This complication to statistical process could also explain why the KDF improved analysis. The KDF converted all variables into an index, making them more computationally similar than the counted census data.

Future analysis should also continue to retest the socioeconomic variables utilized in this study for two important reasons. First, future study of these variables and the inclusion of other census data will better document which variables are most important for identifying vulnerability, particularly between cities. Second, because the census bureau has a habit of changing variable definitions between decadal surveys, the inclusion and consistent retesting of variables will provide a more consistent dataset through future decades of work.

Resolution is another area which requires additional study. Block group explanation of variance was better when the residential boundaries were used (phase II and IV) than political boundaries (phase I and III), which suggests the importance of spatial resolution and focusing on residential areas. Improved spatial resolution data, such as available through the QuickBird satellite or aerial platform sensors, could be used to better understand the influence environmental variables have on the analysis. This is particularly true for LST, which was acquired at 120 square meters by the Landsat 5 TM satellite. Better identification of residential vs. commercial areas could also improve analysis by isolating residential areas better, and not utilizing as much mixed land use areas.

These results demonstrated diverse boundaries and resolutions play an important role in the explanation of variability. Therefore additional boundary tests should be examined in future studies to test their influence on the analysis of vulnerability. Additional studies could be conducted to analyze alternate uses of satellite imagery. NDBI in its binary form, for example, could be beneficial in differentiating built environment from vegetation for a new boundary layer (Jensen 2007, Zha et al. 2003). Another environmental index which could prove beneficial would be the "triangular" index outlined in Voogt and Oke (2003), which "utilizes relations between temperature and NDVI to derive surface fractional vegetative cover of sensible and latent heat (Voogt and Oke 2003)." By combining soil-vegetation and atmosphere transfer data (SVAT), the SVAT index could improve temperature measurements for this type of study. As advances in environmental modeling is made, particularly by models like this one which emphasize the fluctuations of temperature within urban environments, advances to this type of study should also be made to ensure the best resources and data are being used.

The results of this experiment demonstrate that vulnerability can be appropriately analyzed by the procedures outlined in this experiment. Although these conclusions listed many areas which should be further tested and analyzed, those suggestions do not suggest the results were inaccurate. Rather, they only suggest methods which could further improve an analysis of this type. The results outlined in this experiment appropriately demonstrate the spatial vulnerability of Chicago, IL during an EHE, and could be used to advise officials during an impending heat wave.

APPENDIX A

Statistical Output Tables

Phase I

Total Variance of Census Tract Boundary Extraction Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.078	32.42	32.42	9.078	32.42	32.42
2	5.847	20.882	53.302	5.847	20.882	53.302
3	2.598	9.28	62.582	2.598	9.28	62.582
4	2.12	7.572	70.154	2.12	7.572	70.154
5	1.338	4.778	74.932	1.338	4.778	74.932
6	1.042	3.722	78.654	1.042	3.722	78.654
7	1.016	3.628	82.282	1.016	3.628	82.282
8	0.841	3.005	85.287			
9	0.787	2.812	88.098			
10	0.623	2.226	90.325			
11	0.452	1.614	91.939			
12	0.377	1.345	93.284			
13	0.296	1.056	94.34			
14	0.272	0.973	95.313			
15	0.251	0.896	96.209			
16	0.211	0.753	96.962			
17	0.163	0.582	97.544			
18	0.151	0.538	98.082			
19	0.119	0.423	98.505			
20	0.106	0.379	98.884			
21	0.072	0.256	99.14			
22	0.07	0.249	99.389			
23	0.058	0.207	99.596			
24	0.048	0.171	99.767			
25	0.03	0.106	99.873			
26	0.02	0.072	99.945			
27	0.015	0.053	99.999			
28	0	0.001	100			

Extraction Method: Principal Component Analysis.

Phase I

Component Matrix[a] of Census Tract Boundary Test

	Component						
	1	2	3	4	5	6	7
Total Pop	0.952	-0.091	0.118	-0.039	0.045	-0.064	0.074
Male HS Degree	0.872	0.005	0.002	0.009	-0.277	-0.146	0.058
Female HS Degree	0.868	-0.172	-0.092	0.028	-0.295	-0.121	0.046
Male 5 & under	0.842	0.237	0.255	-0.246	0.048	-0.035	0.014
Female age 5 & under	0.829	0.252	0.266	-0.272	0.057	-0.023	0.001
Male age 65 & up	0.772	-0.468	-0.17	0.181	-0.086	-0.035	0.013
Female age 65 & up	0.761	-0.438	-0.258	0.243	-0.086	0.001	-0.033
Female no HS Degree	0.749	0.373	-0.208	-0.092	0.033	-0.126	0.141
Male no HS Degree	0.741	0.365	-0.031	-0.043	-0.06	-0.127	0.158
White pop	0.654	-0.545	0.318	0.208	-0.147	-0.005	-0.021
Female age 65 & up living alone	0.643	-0.41	-0.297	0.398	-0.001	0.035	-0.107
Male age 65 & up living alone	0.627	-0.233	-0.297	0.406	0.122	0.021	-0.11
Pop 65 & up living in Poverty	0.517	0.21	-0.478	0.26	0.344	0.154	-0.07
American Indian pop	0.425	0.284	0.405	0.087	0.033	0.037	-0.14
Asian pop	0.403	-0.189	0.064	0.312	0.089	0.203	0.293
MFI 1999	0.032	-0.791	0.302	-0.07	0.392	-0.149	0.097
MHI 1999	0.075	-0.773	0.374	-0.179	0.33	-0.168	0.13
Pop 5 & under living in Poverty	0.401	0.713	-0.051	-0.295	0.271	0.046	-0.019
PCI 1999	-0.059	-0.7	0.234	0.029	0.533	-0.203	0.132
Below Poverty	0.511	0.674	-0.168	-0.173	0.353	0.057	-0.006
LST	-0.212	0.632	0.117	0.433	0.084	-0.206	0.175
Hispanic pop	0.455	0.463	0.674	0.1	-0.004	0.095	-0.158
Other Race	0.398	0.488	0.668	0.074	0.02	0.098	-0.191
Black pop	0.263	0.37	-0.592	-0.452	0.228	-0.193	0.154
NDBI	-0.316	0.554	0.037	0.627	0.108	-0.206	0.136
NDVI	0.317	-0.585	-0.091	-0.606	-0.153	0.202	-0.12
Pop 65 & up in Group Living	0.137	-0.117	-0.148	0.146	0.378	0.442	-0.441
Hawaiian pop	0.059	0.015	0.12	0.015	-0.025	0.651	0.662

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Phase I Census Tract

Communalities

	Initial	Extraction
Total Pop	1.000	.941
MHI 1999	1.000	.929
Hispanic pop	1.000	.920
MFI 1999	1.000	.908
Female age 65 & up	1.000	.905
Below Poverty	1.000	.902
Female age 5 & under	1.000	.899
NDVI	1.000	.897
Female HS Degree	1.000	.896
Other Race	1.000	.894
Male 5 & under	1.000	.894
PCI 1999	1.000	.892
White pop	1.000	.891
Male age 65 & up	1.000	.885
Hawaiian pop	1.000	.881
Black pop	1.000	.874
NDBI	1.000	.873
Male HS Degree	1.000	.861
Female age 65 & up living alone	1.000	.840
Pop 5 & under living in Poverty	1.000	.835
Female no HS Degree	1.000	.788
Pop 65 & up living in Poverty	1.000	.755
Male no HS Degree	1.000	.730
Male age 65 & up living alone	1.000	.727
LST	1.000	.725
Pop 65 & up in Group Living	1.000	.608
American Indian pop	1.000	.455
Asian pop	1.000	.435

Phase I

Total Variance Explained of Block Group

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.459	26.641	26.641	7.459	26.641	26.641
2	5.291	18.896	45.537	5.291	18.896	45.537
3	2.675	9.552	55.089	2.675	9.552	55.089
4	2.223	7.939	63.028	2.223	7.939	63.028
5	1.351	4.826	67.854	1.351	4.826	67.854
6	1.178	4.208	72.062	1.178	4.208	72.062
7	1.008	3.599	75.661	1.008	3.599	75.661
8	0.935	3.34	79.001			
9	0.878	3.134	82.135			
10	0.83	2.966	85.101			
11	0.69	2.464	87.565			
12	0.511	1.824	89.389			
13	0.41	1.464	90.853			
14	0.378	1.351	92.204			
15	0.365	1.304	93.507			
16	0.32	1.143	94.65			
17	0.27	0.963	95.613			
18	0.226	0.808	96.42			
19	0.209	0.746	97.167			
20	0.203	0.725	97.892			
21	0.161	0.575	98.466			
22	0.131	0.468	98.935			
23	0.086	0.306	99.241			
24	0.072	0.258	99.499			
25	0.059	0.21	99.708			
26	0.047	0.167	99.876			
27	0.034	0.122	99.997			
28	0.001	0.003	100			

Extraction Method: Principal Component Analysis.

Phase I

Component Matrix[a] of Block Group Political Boundaries

	Component						
	1	2	3	4	5	6	7
Total Pop	0.877	0.272	0.207	0.01	0.048	-0.171	-0.001
Male HS Degree	0.768	0.163	0.075	-0.038	-0.333	-0.231	-0.023
Male 5 & under	0.754	-0.097	0.433	-0.142	0.08	-0.053	-0.006
Female HS Degree	0.752	0.355	-0.06	-0.045	-0.316	-0.173	0.011
Female age 5 & under	0.748	-0.107	0.434	-0.161	0.103	-0.032	0.014
Female no HS Degree	0.664	-0.19	-0.097	-0.191	0.034	-0.149	-0.01
Below Poverty	0.66	-0.474	-0.019	-0.265	0.386	0.075	0.001
Male no HS Degree	0.654	-0.164	0.046	-0.084	-0.111	-0.204	-0.022
Female age 65 & up	0.591	0.573	-0.398	0.091	-0.071	0.114	0.005
Pop 65 & up living in Poverty	0.537	0.001	-0.501	-0.014	0.309	0.257	0.001
Female age 65 & up living alone	0.517	0.476	-0.496	0.153	0.034	0.225	-0.015
Male age 65 & up living alone	0.511	0.325	-0.457	0.163	0.115	0.221	-0.029
Asian pop	0.409	0.245	0.04	0.217	0.104	-0.265	0.167
MFI 1999	-0.245	0.747	0.32	0.12	0.383	-0.107	-0.05
MHI 1999	-0.272	0.704	0.439	0.053	0.321	-0.143	-0.046
PCI 1999	-0.222	0.684	0.192	0.186	0.493	-0.126	-0.063
White pop	0.539	0.637	0.239	0.289	-0.115	-0.097	-0.001
LST	0.114	-0.624	-0.141	0.497	0.088	-0.221	-0.018
Male age 65 & up	0.58	0.618	-0.28	0.094	-0.082	0.052	0.011
Pop 5 & under living in Poverty	0.519	-0.529	0.124	-0.331	0.347	0.076	0.008
Hispanic pop	0.515	-0.355	0.542	0.349	-0.061	0.332	-0.018
Other Race	0.453	-0.386	0.528	0.335	-0.047	0.376	-0.031
Black pop	0.309	-0.319	-0.288	-0.636	0.236	-0.263	-0.038
NDVI	-0.11	0.597	0.241	-0.636	-0.159	0.227	0.025
NDBI	0.131	-0.542	-0.28	0.62	0.165	-0.299	-0.019
Pop 65 & up in Group Living	0.115	0.117	-0.156	0.042	0.266	0.338	-0.044
Hawaiian pop	0.046	-0.018	0.082	0.064	0.055	0.093	0.942
American Indian Pop	0.255	-0.127	0.209	0.145	-0.062	0.21	-0.275

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Phase I Block Group

Communalities

	Initial	Extraction
Hispanic pop	1.000	.921
Total Pop	1.000	.918
Hawaiian pop	1.000	.911
NDVI	1.000	.908
MFI 1999	1.000	.896
NDBI	1.000	.890
Other Race	1.000	.890
MHI 1999	1.000	.889
Below Poverty	1.000	.886
Female age 65 & up	1.000	.863
White pop	1.000	.860
PCI 1999	1.000	.852
Female HS Degree	1.000	.828
Female age 65 & up living alone	1.000	.815
Male age 65 & up	1.000	.814
Black pop	1.000	.811
Pop 5 & under living in Poverty	1.000	.801
Female age 5 & under	1.000	.797
Male 5 & under	1.000	.795
Male HS Degree	1.000	.787
LST	1.000	.726
Pop 65 & up living in Poverty	1.000	.700
Male age 65 & up living alone	1.000	.666
Female no HS Degree	1.000	.547
Male no HS Degree	1.000	.518
Asian pop	1.000	.385
American Indian pop	1.000	.269
Pop 65 & up in Group Living	1.000	.240

Phase II

Total Variance of Census Tract Residential Test Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.996	32.128	32.128	8.996	32.128	32.128
2	5.457	19.489	51.617	5.457	19.489	51.617
3	2.59	9.25	60.867	2.59	9.25	60.867
4	2.06	7.358	68.225	2.06	7.358	68.225
5	1.369	4.888	73.112	1.369	4.888	73.112
6	1.038	3.707	76.82	1.038	3.707	76.82
7	1.025	3.66	80.48	1.025	3.66	80.48
8	0.938	3.349	83.829			
9	0.835	2.982	86.811			
10	0.733	2.618	89.43			
11	0.623	2.226	91.656			
12	0.448	1.599	93.255			
13	0.302	1.079	94.334			
14	0.278	0.994	95.328			
15	0.262	0.936	96.264			
16	0.211	0.755	97.018			
17	0.162	0.577	97.596			
18	0.153	0.547	98.142			
19	0.117	0.418	98.561			
20	0.104	0.37	98.93			
21	0.07	0.25	99.18			
22	0.061	0.217	99.398			
23	0.056	0.198	99.596			
24	0.048	0.171	99.767			
25	0.029	0.105	99.872			
26	0.02	0.073	99.945			
27	0.015	0.054	99.999			
28	0	0.001	100			

Extraction Method: Principal Component Analysis.

Phase II

Component Matrix[a] of Census Tract Residential Test

	Component						
	1	2	3	4	5	6	7
Total Pop	0.946	0.14	0.113	-0.044	0.048	0.029	0.022
Male HS Degree	0.872	0.046	-0.004	-0.031	-0.267	0.133	-0.013
Female HS Degree	0.859	0.221	-0.103	-0.04	-0.288	0.112	-0.009
Male 5 & under	0.851	-0.197	0.283	-0.22	0.053	-0.009	-0.011
Female age 5 & under	0.839	-0.214	0.298	-0.242	0.063	-0.022	-0.015
Female no HS Degree	0.767	-0.334	-0.195	-0.136	0.034	0.084	0.046
Male no HS Degree	0.759	-0.324	-0.024	-0.053	-0.051	0.119	0.064
Male age 65 & up	0.749	0.518	-0.205	0.092	-0.099	0.017	-0.006
Female age 65 & up	0.74	0.488	-0.298	0.146	-0.103	-0.013	-0.023
White pop	0.628	0.593	0.275	0.21	-0.148	0.017	-0.014
Female age 65 & up living alone	0.624	0.45	-0.353	0.334	-0.021	-0.028	-0.071
Male age 65 & up living alone	0.616	0.271	-0.35	0.368	0.103	-0.024	-0.087
Pop 65 & up living in Poverty	0.528	-0.187	-0.503	0.23	0.318	-0.146	0.004
American Indian pop	0.441	-0.249	0.398	0.153	0.021	-0.05	-0.102
Asian pop	0.396	0.223	0.02	0.322	0.076	-0.084	0.329
MFI 1999	-0.006	0.802	0.285	-0.085	0.393	0.041	-0.018
MHI 1999	0.038	0.79	0.37	-0.209	0.331	0.048	0.001
Pop 5 & under living in Poverty	0.432	-0.714	-0.003	-0.233	0.28	-0.061	-0.003
PCI 1999	-0.092	0.708	0.206	0.03	0.535	0.083	-0.026
Below Poverty	0.541	-0.668	-0.135	-0.122	0.356	-0.072	0.007
Hispanic pop	0.482	-0.417	0.667	0.211	-0.014	-0.075	-0.08
Other Race	0.426	-0.448	0.665	0.19	0.01	-0.085	-0.106
Black pop	0.275	-0.388	-0.531	-0.523	0.243	0.086	0.015
NDVI	0.222	0.533	0	-0.681	-0.146	-0.087	0.027
NDBI	-0.228	-0.505	-0.06	0.681	0.15	0.242	0.026
LST	0.079	-0.027	0.028	0.035	0.262	0.723	0.218
Pop 65 & up in Group Living	0.131	0.123	-0.166	0.141	0.335	-0.504	-0.142
Hawaiian pop	0.06	-0.009	0.118	0.037	-0.022	-0.265	0.893

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Phase II Census Tract

Communalities

	Initial	Extraction
Total Pop	1.000	.932
MHI 1999	1.000	.917
Hispanic pop	1.000	.908
Female age 65 & up	1.000	.908
Below Poverty	1.000	.903
Female age 5 & under	1.000	.902
Male 5 & under	1.000	.896
Female HS Degree	1.000	.895
Male age 65 & up	1.000	.890
MFI 1999	1.000	.889
White pop	1.000	.889
Hawaiian pop	1.000	.887
Other Race	1.000	.879
NDBI	1.000	.856
Male HS Degree	1.000	.852
Black pop	1.000	.848
PCI 1999	1.000	.847
Female age 65 & up living alone	1.000	.834
Pop 5 & under living in Poverty	1.000	.833
NDVI	1.000	.827
Female no HS Degree	1.000	.767
Pop 65 & up living in Poverty	1.000	.742
Male age 65 & up living alone	1.000	.730
Male no HS Degree	1.000	.706
LST	1.000	.647
Pop 65 & up in Group Living	1.000	.466
American Indian pop	1.000	.452
Asian pop	1.000	.431

Phase II

Total Variance of Block Group Residential Test Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.469	26.675	26.675	7.469	26.675	26.675
2	4.953	17.691	44.366	4.953	17.691	44.366
3	2.672	9.542	53.909	2.672	9.542	53.909
4	2.006	7.163	61.072	2.006	7.163	61.072
5	1.349	4.816	65.888	1.349	4.816	65.888
6	1.125	4.019	69.907	1.125	4.019	69.907
7	1.009	3.603	73.51	1.009	3.603	73.51
8	1.005	3.588	77.098	1.005	3.588	77.098
9	0.934	3.336	80.434			
10	0.877	3.132	83.567			
11	0.797	2.846	86.413			
12	0.685	2.446	88.859			
13	0.503	1.797	90.656			
14	0.394	1.407	92.063			
15	0.377	1.346	93.409			
16	0.348	1.241	94.65			
17	0.276	0.985	95.635			
18	0.234	0.835	96.471			
19	0.209	0.747	97.217			
20	0.204	0.728	97.945			
21	0.151	0.539	98.484			
22	0.132	0.471	98.955			
23	0.084	0.3	99.255			
24	0.068	0.242	99.497			
25	0.059	0.21	99.707			
26	0.047	0.168	99.875			
27	0.034	0.122	99.997			
28	0.001	0.003	100			

Extraction Method: Principal Component Analysis.

Phase II

Component Matrix[a] of Block Group Residential Test

	Component							
	1	2	3	4	5	6	7	8
Total Pop	0.874	0.273	0.219	0.054	0.029	-0.162	-0.02	-0.036
Male HS Degree	0.765	0.163	0.08	0.079	-0.363	-0.164	0.015	-0.017
Male 5 & under	0.751	-0.117	0.423	0.19	0.065	-0.024	-0.016	-0.027
Female HS Degree	0.749	0.361	-0.049	0.096	-0.345	-0.096	-0.013	0.008
Female age 5 & under	0.744	-0.129	0.422	0.208	0.089	-0.002	-0.03	-0.009
Female no HS Degree	0.663	-0.194	-0.113	0.196	0.009	-0.114	0.014	-0.001
Below Poverty	0.662	-0.496	-0.054	0.211	0.394	0.027	-0.017	-0.026
Male no HS Degree	0.652	-0.167	0.038	0.09	-0.133	-0.179	0.023	-0.015
Pop 65 & up living in Poverty	0.537	0.014	-0.501	-0.046	0.335	0.2	0.003	0.009
Female age 65 & up living alone	0.516	0.5	-0.471	-0.175	0.059	0.202	0.019	0.009
Male age 65 & up living alone	0.511	0.348	-0.436	-0.2	0.144	0.169	0.031	-0.008
Asian pop	0.409	0.263	0.065	-0.188	0.099	-0.366	-0.184	-0.007
American Indian pop	0.254	-0.126	0.214	-0.168	-0.034	0.184	0.236	-0.144
MFI 1999	-0.255	0.755	0.349	0.018	0.363	-0.1	0.062	-0.009
PCI 1999	-0.227	0.705	0.226	-0.068	0.473	-0.146	0.029	-0.076
MHI 1999	-0.281	0.703	0.463	0.102	0.287	-0.106	0.046	-0.017
White pop	0.535	0.655	0.281	-0.207	-0.118	-0.097	-0.02	-0.032
Male age 65 & up	0.575	0.639	-0.253	-0.049	-0.085	0.086	0	0.027
Female age 65 & up	0.587	0.597	-0.372	-0.066	-0.068	0.148	0.007	0.031
Pop 5 & under living in Poverty	0.52	-0.56	0.081	0.289	0.35	0.053	-0.022	-0.015
Hispanic pop	0.515	-0.344	0.561	-0.367	-0.017	0.295	0.026	0.021
Other Race	0.452	-0.377	0.544	-0.361	-0.001	0.341	0.041	0.021
NDVI	-0.181	0.495	0.195	0.673	-0.168	0.308	0.043	0.119
NDBI	0.206	-0.454	-0.236	-0.641	0.166	-0.399	0.054	0.001
Black pop	0.307	-0.354	-0.344	0.629	0.186	-0.197	0.032	-0.025
Pop 65 & up in Group Living	0.114	0.125	-0.148	-0.046	0.284	0.368	0.038	0.028
Hawaiian pop	0.046	-0.016	0.085	-0.068	0.069	0.045	-0.691	0.647
LST	0.096	-0.033	0.017	-0.019	0.032	-0.145	0.648	0.732

Extraction Method: Principal Component Analysis.

a. 8 components extracted.

Phase II Block Group

Communalities

	Initial	Extraction
LST	1.000	.989
Hispanic pop	1.000	.922
Total Pop	1.000	.919
Hawaiian pop	1.000	.918
NDVI	1.000	.908
NDBI	1.000	.906
MFI 1999	1.000	.903
MHI 1999	1.000	.894
Other Race	1.000	.892
Below Poverty	1.000	.888
Female age 65 & up	1.000	.871
White pop	1.000	.862
PCI 1999	1.000	.856
Female HS Degree	1.000	.831
Male age 65 & up	1.000	.820
Female age 65 & up living alone	1.000	.813
Black pop	1.000	.809
Pop 5 & under living in Poverty	1.000	.801
Female age 5 & under	1.000	.801
Male 5 & under	1.000	.798
Male HS Degree	1.000	.784
Pop 65 & up living in Poverty	1.000	.694
Male age 65 & up living alone	1.000	.662
Female no HS Degree	1.000	.542
Male no HS Degree	1.000	.514
Asian pop	1.000	.454
Pop 65 & up in Group Living	1.000	.271
American Indian pop	1.000	.266

Phase III

Total Variance of KDF Variables at the Census Tract Boundary Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.662	48.793	48.793	13.662	48.793	48.793
2	4.428	15.814	64.607	4.428	15.814	64.607
3	2.972	10.615	75.222	2.972	10.615	75.222
4	1.971	7.04	82.262	1.971	7.04	82.262
5	1.441	5.146	87.409	1.441	5.146	87.409
6	0.838	2.994	90.403			
7	0.704	2.516	92.919			
8	0.55	1.963	94.881			
9	0.445	1.591	96.472			
10	0.204	0.73	97.202			
11	0.175	0.626	97.828			
12	0.134	0.479	98.307			
13	0.093	0.333	98.64			
14	0.077	0.273	98.913			
15	0.067	0.241	99.154			
16	0.053	0.191	99.344			
17	0.041	0.148	99.492			
18	0.038	0.134	99.626			
19	0.03	0.108	99.734			
20	0.024	0.084	99.818			
21	0.016	0.058	99.876			
22	0.01	0.035	99.911			
23	0.007	0.027	99.938			
24	0.007	0.023	99.962			
25	0.005	0.018	99.98			
26	0.003	0.011	99.991			
27	0.002	0.009	100			
28	8.40E-05	0	100			

Extraction Method: Principal Component Analysis.

Phase III

Component Matrix[a] for KDF Variables at the Census Tract Boundary

	Component				
	1	2	3	4	5
Total Pop	0.959	0.114	0.12	0.072	0.135
Male no HS Degree	0.902	-0.34	-0.074	0.059	0.014
Female age 5 & under	0.889	-0.395	0.075	-0.013	0.128
Male 5 & under	0.884	-0.406	0.088	0.01	0.125
Male HS Degree	0.869	-0.225	-0.004	0.273	-0.126
Female no HS Degree	0.86	-0.32	-0.329	-0.009	0.055
Below Poverty	0.835	-0.28	-0.243	-0.221	0.217
Female HS Degree	0.825	-0.176	-0.218	0.311	-0.141
Pop 65 & up living in Poverty	0.785	0.141	-0.445	-0.082	0.077
Male age 65 & up	0.773	0.347	-0.241	0.369	-0.089
American Indian pop	0.751	-0.272	0.463	0.144	-0.023
Female age 65 & up	0.737	0.367	-0.352	0.37	-0.107
LST	0.729	-0.071	0.021	-0.308	-0.358
Pop 5 & under living in Poverty	0.729	-0.469	-0.235	-0.252	0.206
Male age 65 & up living alone	0.709	0.539	-0.238	0.097	-0.01
Hispanic pop	0.653	-0.425	0.586	0.089	-0.026
Other Race	0.626	-0.464	0.576	0.051	0.007
NDVI	-0.601	-0.119	-0.076	0.484	0.552
MHI 1999	0.596	0.547	0.271	-0.378	0.264
Hawaiian pop	0.512	-0.193	0.46	0.089	0.168
Asian pop	0.38	0.371	0.038	0.352	-0.261
PCI 1999	0.468	0.714	0.221	-0.357	0.254
MFI 1999	0.523	0.648	0.243	-0.377	0.266
Female age 65 & up living alone	0.607	0.608	-0.283	0.258	-0.096
White pop	0.519	0.576	0.528	0.236	-0.015
Pop 65 & up in Group Living	0.299	0.516	0.075	0.117	0.242
Black pop	0.396	-0.242	-0.761	-0.266	0.272
NDBI	0.531	0.096	-0.011	-0.527	-0.599

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Phase III Census Tract

Communalities

	Initial	Extraction
Total Pop	1.000	.971
PCI 1999	1.000	.970
Male 5 & under	1.000	.970
Female age 5 & under	1.000	.968
MFI 1999	1.000	.966
Hispanic pop	1.000	.959
Female no HS Degree	1.000	.953
Female age 65 & up	1.000	.951
Other Race	1.000	.941
MHI 1999	1.000	.940
Male no HS Degree	1.000	.939
Black pop	1.000	.939
White pop	1.000	.937
Below Poverty	1.000	.931
NDBI	1.000	.928
NDVI	1.000	.920
Male age 65 & up	1.000	.920
Pop 5 & under living in Poverty	1.000	.912
Male HS Degree	1.000	.896
Female age 65 & up living alone	1.000	.894
Female HS Degree	1.000	.875
American Indian pop	1.000	.873
Male age 65 & up living alone	1.000	.859
Pop 65 & up living in Poverty	1.000	.846
LST	1.000	.761
Hawaiian pop	1.000	.547
Asian pop	1.000	.475
Pop 65 & up in Group Living	1.000	.434

Phase III

Total Variance of KDF Variables Extracted from Block Group Boundaries Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.85	63.748	63.748	17.85	63.748	63.748
2	2.445	8.733	72.482	2.445	8.733	72.482
3	1.637	5.846	78.328	1.637	5.846	78.328
4	1.371	4.898	83.225	1.371	4.898	83.225
5	0.966	3.449	86.674			
6	0.775	2.767	89.441			
7	0.722	2.58	92.021			
8	0.494	1.766	93.787			
9	0.42	1.499	95.286			
10	0.371	1.326	96.612			
11	0.254	0.909	97.52			
12	0.159	0.569	98.09			
13	0.103	0.368	98.458			
14	0.087	0.311	98.769			
15	0.085	0.303	99.072			
16	0.064	0.229	99.302			
17	0.047	0.167	99.469			
18	0.042	0.151	99.62			
19	0.03	0.107	99.727			
20	0.029	0.104	99.831			
21	0.012	0.042	99.873			
22	0.011	0.038	99.911			
23	0.008	0.029	99.94			
24	0.006	0.022	99.962			
25	0.005	0.017	99.979			
26	0.003	0.012	99.991			
27	0.002	0.008	100			
28	5.27E-05	0	100			

Extraction Method: Principal Component Analysis.

Phase III

Component Matrix[a] of KDF Variables from Block Group Boundaries

	Component			
	1	2	3	4
Total Pop	0.982	-0.073	0.08	0.042
Female age 5 & under	0.964	0.076	0.039	-0.022
Male 5 & under	0.962	0.072	0.033	-0.011
Male HS Degree	0.947	-0.116	0.022	-0.029
Female no HS Degree	0.935	0.085	0.021	-0.223
Male no HS Degree	0.931	0.156	0.03	-0.109
Female HS Degree	0.924	-0.249	0.02	-0.066
MFI 1999	0.912	-0.207	0.035	0.056
Male age 65 & up	0.912	-0.352	0.035	-0.043
MHI 1999	0.91	-0.199	0.023	0.036
Female age 65 & up	0.908	-0.364	0.044	-0.051
PCI 1999	0.893	-0.192	0.062	0.088
Female age 65 & up living alone	0.874	-0.36	0.087	-0.015
Male age 65 & up living alone	0.868	-0.198	0.115	-0.086
White pop	0.868	-0.312	0.115	0.295
Pop 65 & up living in Poverty	0.817	0.108	0.038	-0.247
Below Poverty	0.781	0.487	0.048	-0.235
Pop 5 & under living in Poverty	0.714	0.571	0.007	-0.268
American Indian pop	0.689	0.312	0.187	0.29
Hispanic pop	0.682	0.566	0.145	0.359
LST	0.681	0.085	-0.512	0.099
Asian pop	0.52	-0.205	0.216	0.324
Hawaiian pop	0.39	0.384	0.113	0.06
Pop 65 & up in Group Living	0.382	-0.239	0.062	0.11
Other Race	0.609	0.645	0.15	0.356
NDBI	0.505	0.048	-0.794	0.201
NDVI	-0.604	-0.017	0.728	-0.152
Black pop	0.638	0.128	-0.119	-0.684

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Phase III Block Group

Communalities

	Initial	Extraction
Total Pop	1.000	.978
Female age 65 & up	1.000	.962
Male age 65 & up	1.000	.958
White pop	1.000	.951
Female age 5 & under	1.000	.938
Hispanic pop	1.000	.936
Other Race	1.000	.936
Female no HS Degree	1.000	.932
Male 5 & under	1.000	.931
NDBI	1.000	.928
Female HS Degree	1.000	.921
NDVI	1.000	.919
Male HS Degree	1.000	.911
Pop 5 & under living in Poverty	1.000	.906
Black pop	1.000	.905
Below Poverty	1.000	.904
Male no HS Degree	1.000	.904
Female age 65 & up living alone	1.000	.900
MFI 1999	1.000	.879
MHI 1999	1.000	.870
PCI 1999	1.000	.845
Male age 65 & up living alone	1.000	.813
LST	1.000	.743
Pop 65 & up living in Poverty	1.000	.741
American Indian pop	1.000	.692
Asian pop	1.000	.464
Hawaiian pop	1.000	.316
Pop 65 & up in Group Living	1.000	.219

Phase IV

Total Variance of KDF Variables Extracted from Census Tract Residential Boundaries Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.258	47.349	47.349	13.258	47.349	47.349
2	4.541	16.218	63.567	4.541	16.218	63.567
3	2.981	10.646	74.213	2.981	10.646	74.213
4	1.874	6.693	80.906	1.874	6.693	80.906
5	1.188	4.241	85.147	1.188	4.241	85.147
6	0.973	3.475	88.622			
7	0.774	2.764	91.386			
8	0.69	2.465	93.851			
9	0.532	1.9	95.751			
10	0.407	1.453	97.204			
11	0.175	0.627	97.83			
12	0.137	0.49	98.32			
13	0.096	0.342	98.663			
14	0.082	0.292	98.954			
15	0.055	0.198	99.152			
16	0.051	0.181	99.333			
17	0.042	0.149	99.483			
18	0.038	0.135	99.618			
19	0.031	0.112	99.73			
20	0.024	0.086	99.816			
21	0.016	0.059	99.875			
22	0.01	0.035	99.91			
23	0.008	0.027	99.937			
24	0.007	0.024	99.961			
25	0.005	0.019	99.979			
26	0.003	0.012	99.991			
27	0.002	0.009	100			
28	8.57E-05	0	100			

Extraction Method: Principal Component Analysis.

Phase IV

Component Matrix[a] of KDF Variables from Census Tract Residential Boundaries

	Component				
	1	2	3	4	5
Total Pop	0.963	0.096	0.13	0.021	0.139
Male no HS Degree	0.894	-0.36	-0.075	0.047	0.017
Female age 5 & under	0.879	-0.419	0.078	-0.067	0.101
Male 5 & under	0.874	-0.431	0.091	-0.044	0.102
Male HS Degree	0.859	-0.245	0.001	0.305	-0.01
Female no HS Degree	0.852	-0.335	-0.332	-0.022	0.053
Below Poverty	0.833	-0.293	-0.247	-0.297	0.07
Female HS Degree	0.814	-0.191	-0.213	0.355	0.006
Pop 65 & up living in Poverty	0.79	0.135	-0.444	-0.109	-0.011
Male age 65 & up	0.775	0.34	-0.223	0.391	0.04
American Indian pop	0.745	-0.292	0.468	0.117	-0.021
Female age 65 & up	0.74	0.362	-0.336	0.399	0.031
Male age 65 & up living alone	0.721	0.534	-0.226	0.088	-0.031
Pop 5 & under living in Poverty	0.721	-0.48	-0.241	-0.324	0.053
NDVI	-0.686	-0.192	-0.036	0.254	0.573
Hispanic pop	0.644	-0.447	0.584	0.06	-0.054
Female age 65 & up living alone	0.621	0.603	-0.268	0.269	-0.047
Other Race	0.616	-0.484	0.574	0.012	-0.04
MHI 1999	0.595	0.543	0.272	-0.431	0.171
Hawaiian pop	0.511	-0.217	0.464	0.014	0.094
PCI 1999	0.476	0.71	0.222	-0.406	0.152
MFI 1999	0.526	0.645	0.243	-0.43	0.165
White pop	0.527	0.561	0.542	0.223	0.059
Pop 65 & up in Group Living	0.314	0.499	0.093	0.038	0.329
Black pop	0.385	-0.24	-0.767	-0.317	0.22
Asian pop	0.391	0.362	0.045	0.394	-0.254
NDBI	0.582	0.176	-0.072	-0.336	-0.67
LST	0.153	-0.017	-0.003	-0.099	-0.188

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Phase IV Census Tract

Communalities

	Initial	Extraction
Total Pop	1.000	.972
Male 5 & under	1.000	.970
Female age 5 & under	1.000	.968
PCI 1999	1.000	.968
MFI 1999	1.000	.965
Hispanic pop	1.000	.962
Female age 65 & up	1.000	.953
Female no HS Degree	1.000	.951
Other Race	1.000	.944
Black pop	1.000	.944
White pop	1.000	.939
MHI 1999	1.000	.937
Male no HS Degree	1.000	.937
NDBI	1.000	.937
Below Poverty	1.000	.935
Male age 65 & up	1.000	.921
Pop 5 & under living in Poverty	1.000	.917
NDVI	1.000	.901
Female age 65 & up living alone	1.000	.895
Male HS Degree	1.000	.890
American Indian pop	1.000	.874
Female HS Degree	1.000	.871
Male age 65 & up living alone	1.000	.865
Pop 65 & up living in Poverty	1.000	.851
Hawaiian pop	1.000	.533
Asian pop	1.000	.506
Pop 65 & up in Group Living	1.000	.466
LST	1.000	.069

Phase IV

Total Variance of KDF Variables at the Block Group Residential Trial Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.424	62.228	62.228	17.424	62.228	62.228
2	2.467	8.811	71.039	2.467	8.811	71.039
3	1.449	5.175	76.214	1.449	5.175	76.214
4	1.279	4.567	80.781	1.279	4.567	80.781
5	1.001	3.574	84.356	1.001	3.574	84.356
6	0.961	3.431	87.786			
7	0.769	2.746	90.532			
8	0.726	2.594	93.126			
9	0.498	1.778	94.904			
10	0.411	1.466	96.37			
11	0.318	1.137	97.507			
12	0.163	0.583	98.09			
13	0.105	0.374	98.463			
14	0.086	0.306	98.769			
15	0.084	0.299	99.068			
16	0.062	0.223	99.291			
17	0.048	0.171	99.462			
18	0.043	0.153	99.615			
19	0.03	0.108	99.723			
20	0.03	0.106	99.829			
21	0.012	0.042	99.871			
22	0.011	0.039	99.91			
23	0.008	0.029	99.939			
24	0.006	0.023	99.962			
25	0.005	0.018	99.979			
26	0.003	0.012	99.991			
27	0.002	0.008	100			
28	5.30E-05	0	100			

Extraction Method: Principal Component Analysis.

Phase IV

Component Matrix[a] of KDF Block Group Residential Trial

	Component				
	1	2	3	4	5
Total Pop	0.984	-0.066	0.074	-0.003	0.006
Female age 5 & under	0.965	0.083	-0.011	0	0.039
Male 5 & under	0.963	0.08	-0.008	-0.01	0.035
Male HS Degree	0.947	-0.11	-0.012	0.017	0.034
Female no HS Degree	0.935	0.094	-0.143	0.168	-0.032
Male no HS Degree	0.93	0.166	-0.06	0.085	-0.025
Female HS Degree	0.925	-0.245	-0.034	0.048	0.034
Male age 65 & up	0.913	-0.351	0.001	0.05	0.013
MFI 1999	0.912	-0.203	0.055	-0.044	0.091
MHI 1999	0.91	-0.197	0.028	-0.043	0.105
Female age 65 & up	0.91	-0.361	0.005	0.068	0.003
PCI 1999	0.893	-0.187	0.099	-0.045	0.074
Female age 65 & up living alone	0.875	-0.354	0.07	0.085	-0.029
White pop	0.869	-0.306	0.275	-0.163	0.018
Male age 65 & up living alone	0.867	-0.19	0.051	0.172	-0.078
Pop 65 & up living in Poverty	0.815	0.115	-0.129	0.231	-0.153
Below Poverty	0.777	0.496	-0.136	0.198	-0.105
Pop 5 & under living in Poverty	0.71	0.578	-0.198	0.178	-0.062
American Indian pop	0.686	0.324	0.33	-0.093	-0.031
Hispanic pop	0.676	0.577	0.313	-0.221	-0.012
Black pop	0.637	0.131	-0.556	0.413	0.02
NDVI	-0.617	0.039	0.472	0.575	0.074
Asian pop	0.519	-0.196	0.393	-0.064	-0.159
Hawaiian pop	0.393	0.384	0.08	-0.051	0.157
Pop 65 & up in Group Living	0.385	-0.229	0.107	-0.037	-0.284
Other Race	0.603	0.655	0.313	-0.216	-0.014
NDBI	0.523	-0.006	-0.483	-0.643	0.107
LST	0.143	0.026	0.07	0.113	0.88

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

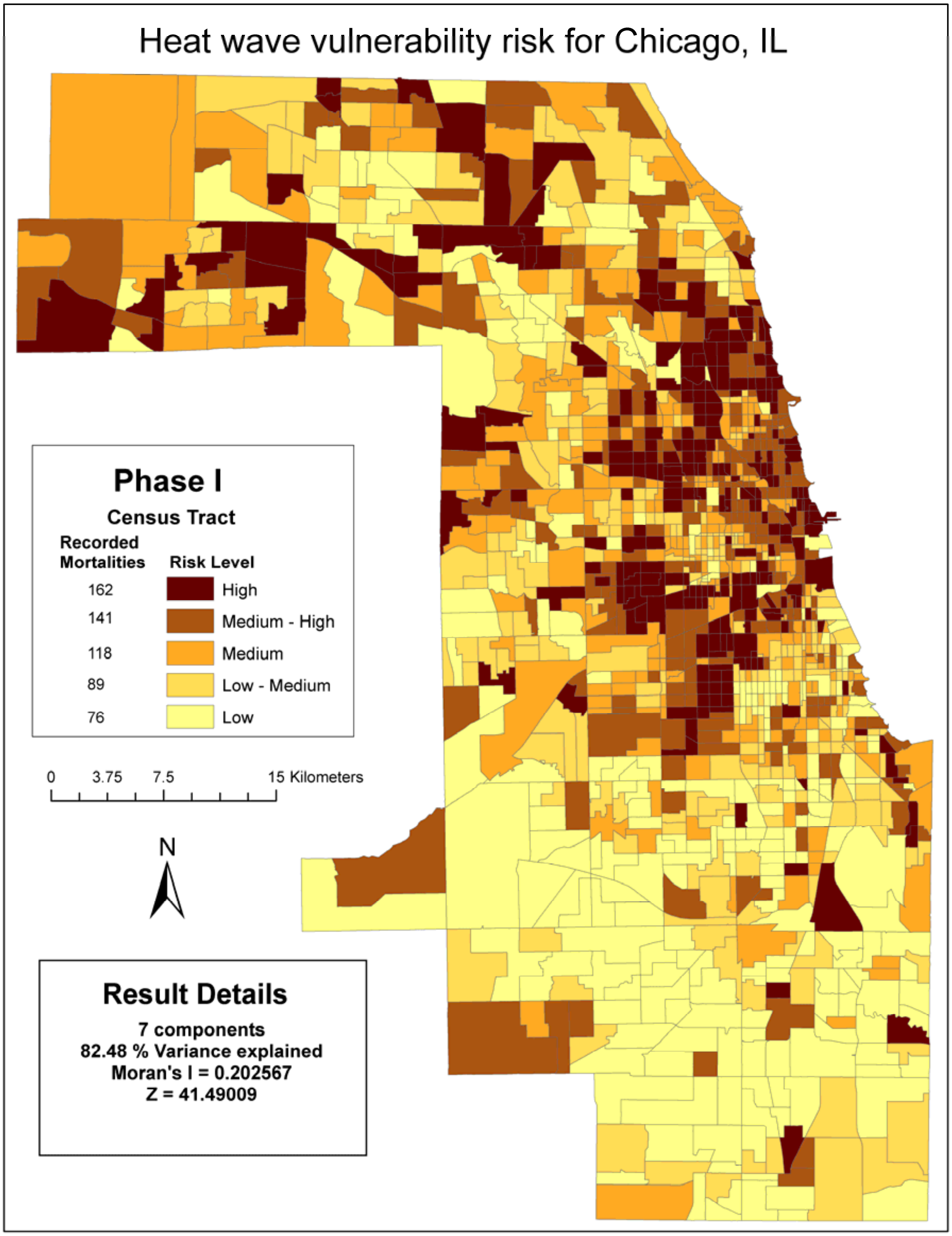
Phase IV Block Group

Communalities

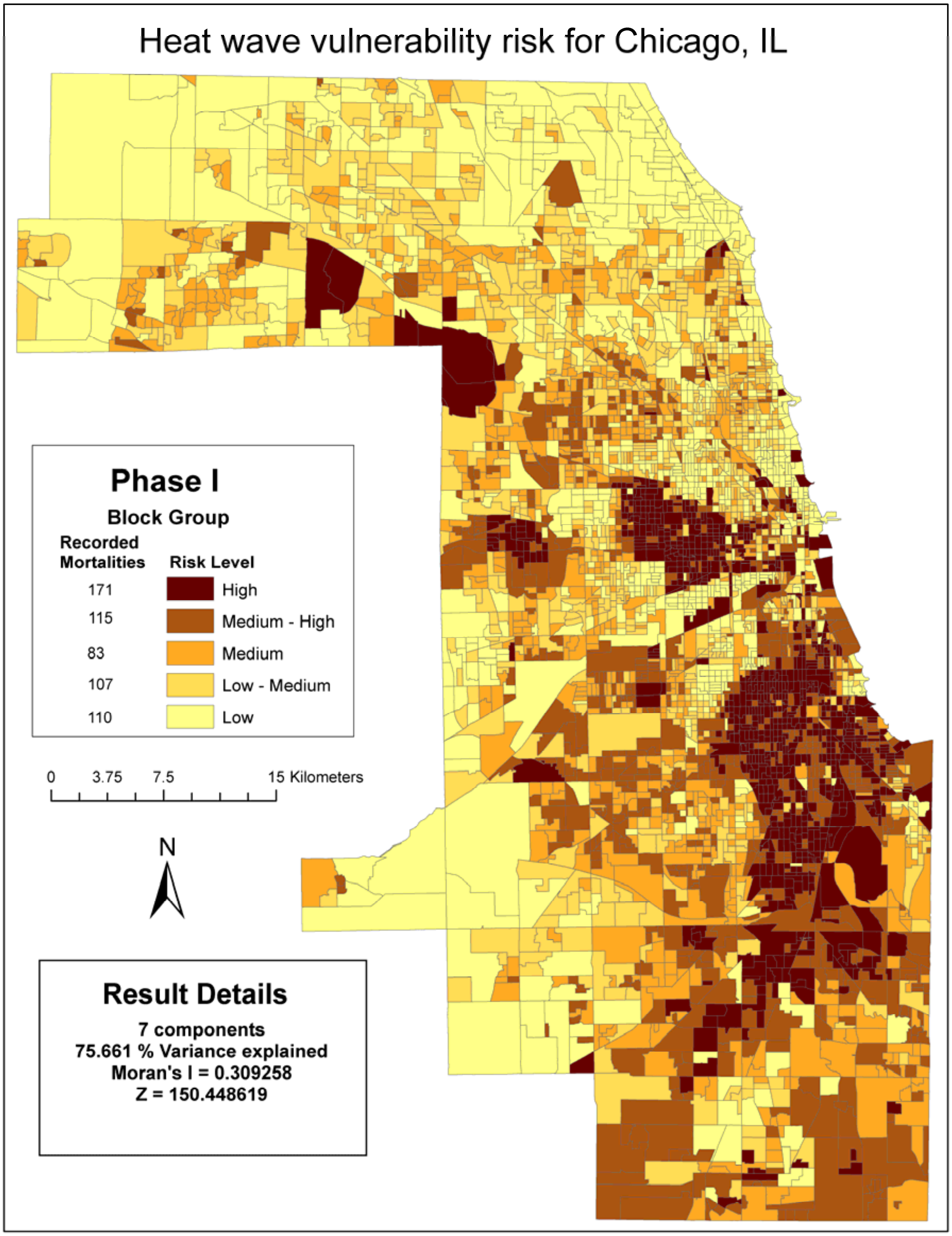
	Initial	Extraction
Total Pop	1.000	.978
Female age 65 & up	1.000	.962
Male age 65 & up	1.000	.959
White pop	1.000	.951
NDVI	1.000	.942
Female age 5 & under	1.000	.941
Hispanic pop	1.000	.937
Other Race	1.000	.937
Male 5 & under	1.000	.935
NDBI	1.000	.933
Female no HS Degree	1.000	.933
Female HS Degree	1.000	.921
Below Poverty	1.000	.919
Pop 5 & under living in Poverty	1.000	.912
Male HS Degree	1.000	.911
Male no HS Degree	1.000	.904
Female age 65 & up living alone	1.000	.903
Black pop	1.000	.902
MFI 1999	1.000	.887
MHI 1999	1.000	.880
PCI 1999	1.000	.850
Male age 65 & up living alone	1.000	.827
LST	1.000	.813
Pop 65 & up living in Poverty	1.000	.770
American Indian pop	1.000	.694
Asian pop	1.000	.491
Hawaiian pop	1.000	.335
Pop 65 & up in Group Living	1.000	.294

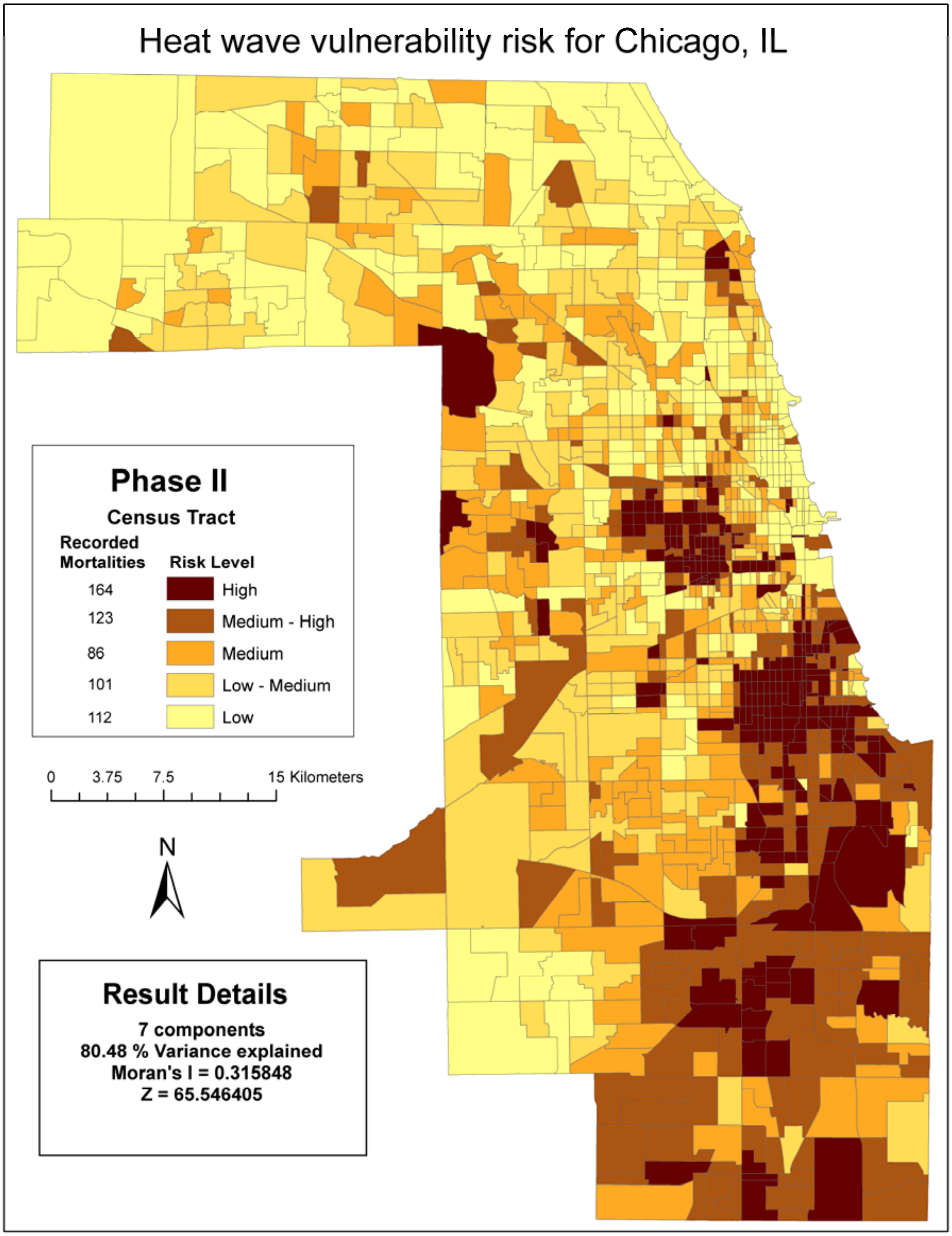
APPENDIX B

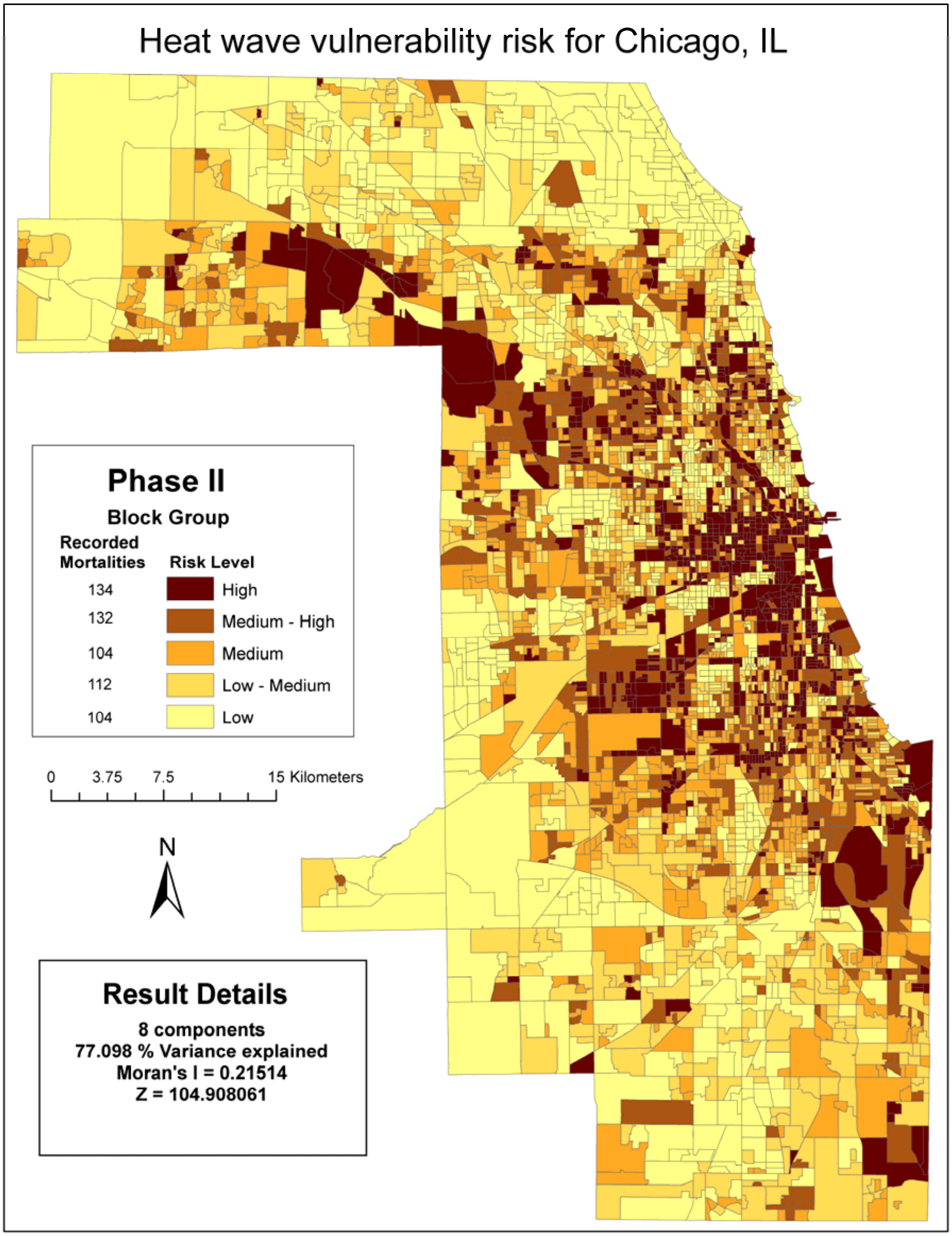
Vulnerability Maps Summation of all Components

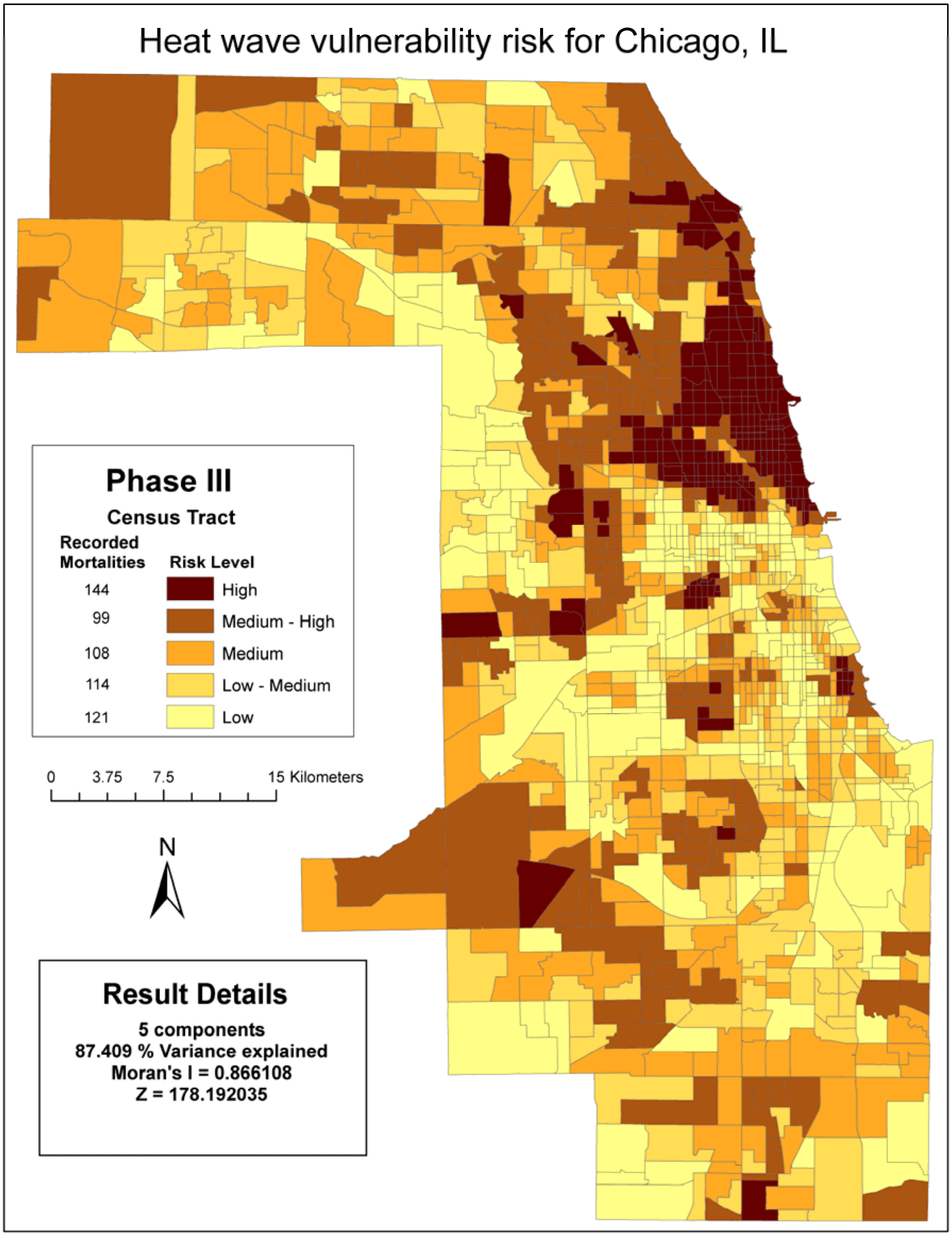


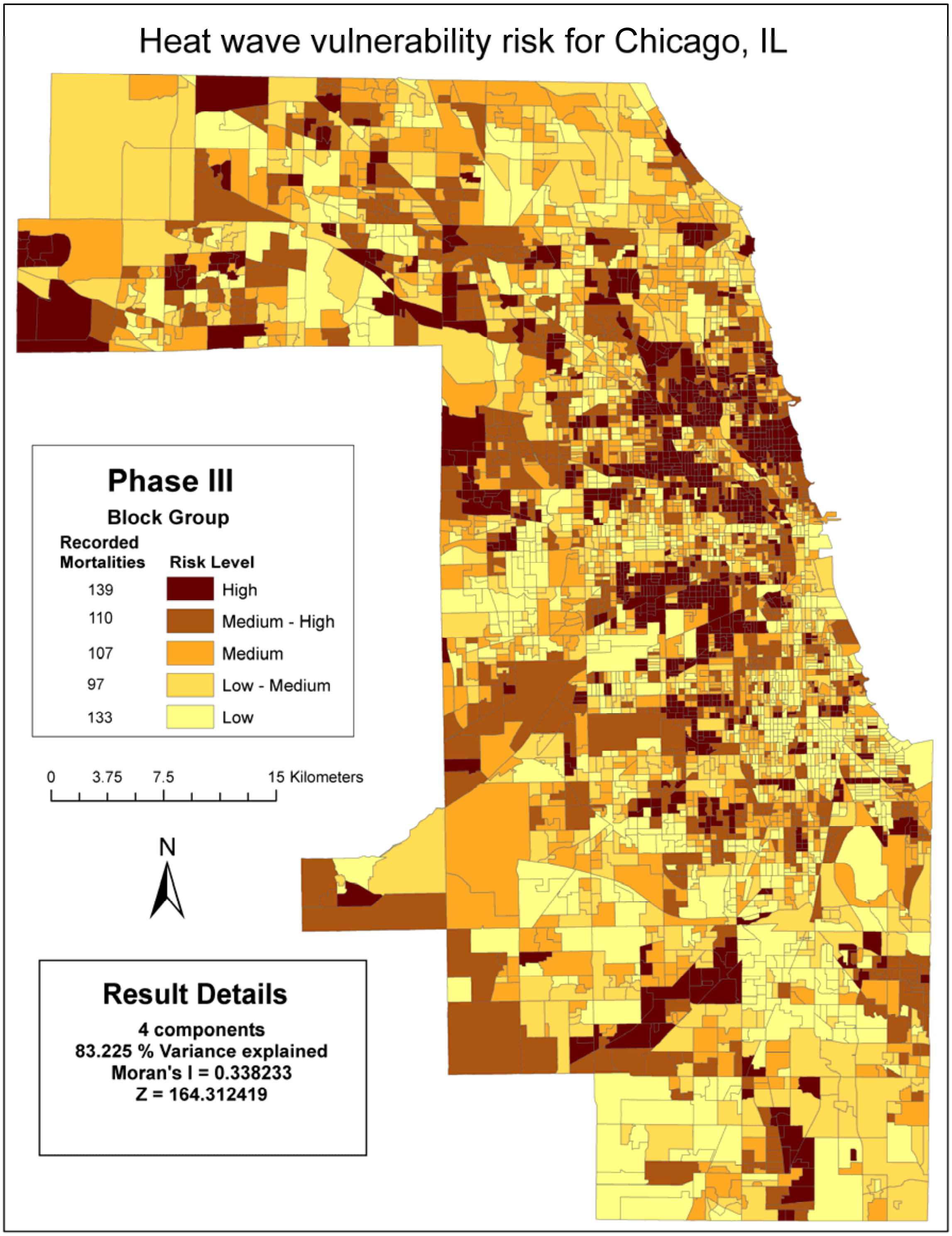
Heat wave vulnerability risk for Chicago, IL
Phase I
Census Tract
Recorded Mortalities
Risk Level
162
High
141
Medium - High
118
Medium
89
Low - Medium
76
Low
0
3.75
7.5
15 Kilometers
N
Result Details
7 components
82.48 % Variance explained
Moran's I = 0.202567
Z = 41.49009

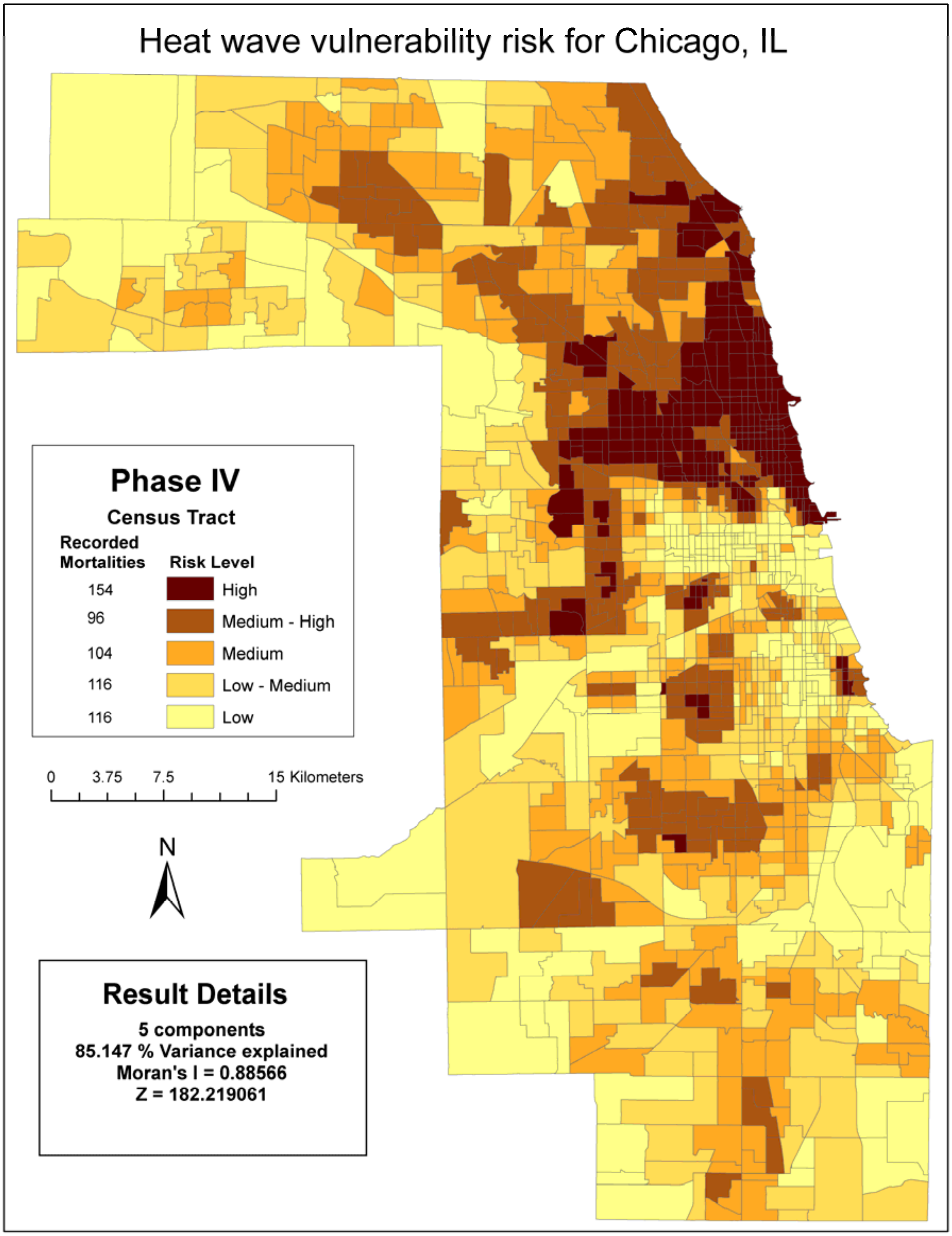

Heat wave vulnerability risk for Chicago, IL
Phase I
Block Group
Recorded Mortalities
Risk Level
171
High
115
Medium - High
83
Medium
107
Low - Medium
110
Low
0
3.75
7.5
15 Kilometers
N
Result Details
7 components
75.661 % Variance explained
Moran's I = 0.309258
Z = 150.448619

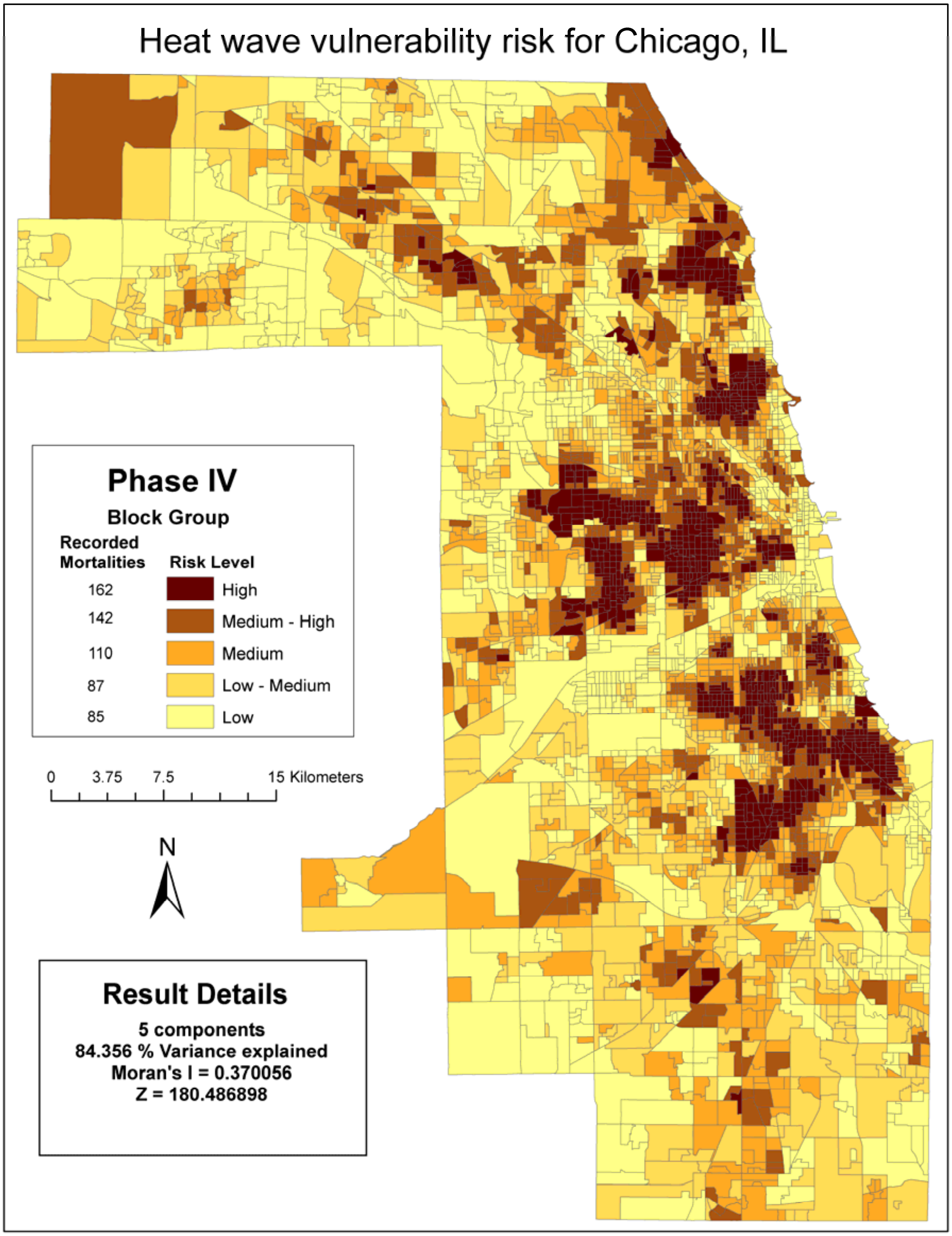

Heat wave vulnerability risk for Chicago, IL
Phase II
Census Tract
Recorded Mortalities
Risk Level
164
High
123
Medium - High
86
Medium
101
Low - Medium
112
Low
0
3.75
7.5
15 Kilometers
N
Result Details
7 components
80.48 % Variance explained
Moran's I = 0.315848
Z = 65.546405


Heat wave vulnerability risk for Chicago, IL
Phase II
Block Group
Recorded Mortalities
Risk Level
134
High
132
Medium - High
104
Medium
112
Low - Medium
104
Low
0
3.75
7.5
15 Kilometers
N
Result Details
8 components
77.098 % Variance explained
Moran's I = 0.21514
Z = 104.908061


Heat wave vulnerability risk for Chicago, IL
Phase III
Census Tract
Recorded Mortalities
Risk Level
144
High
99
Medium - High
108
Medium
114
Low - Medium
121
Low
0
3.75
7.5
15 Kilometers
N
Result Details
5 components
87.409 % Variance explained
Moran's I = 0.866108
Z = 178.192035

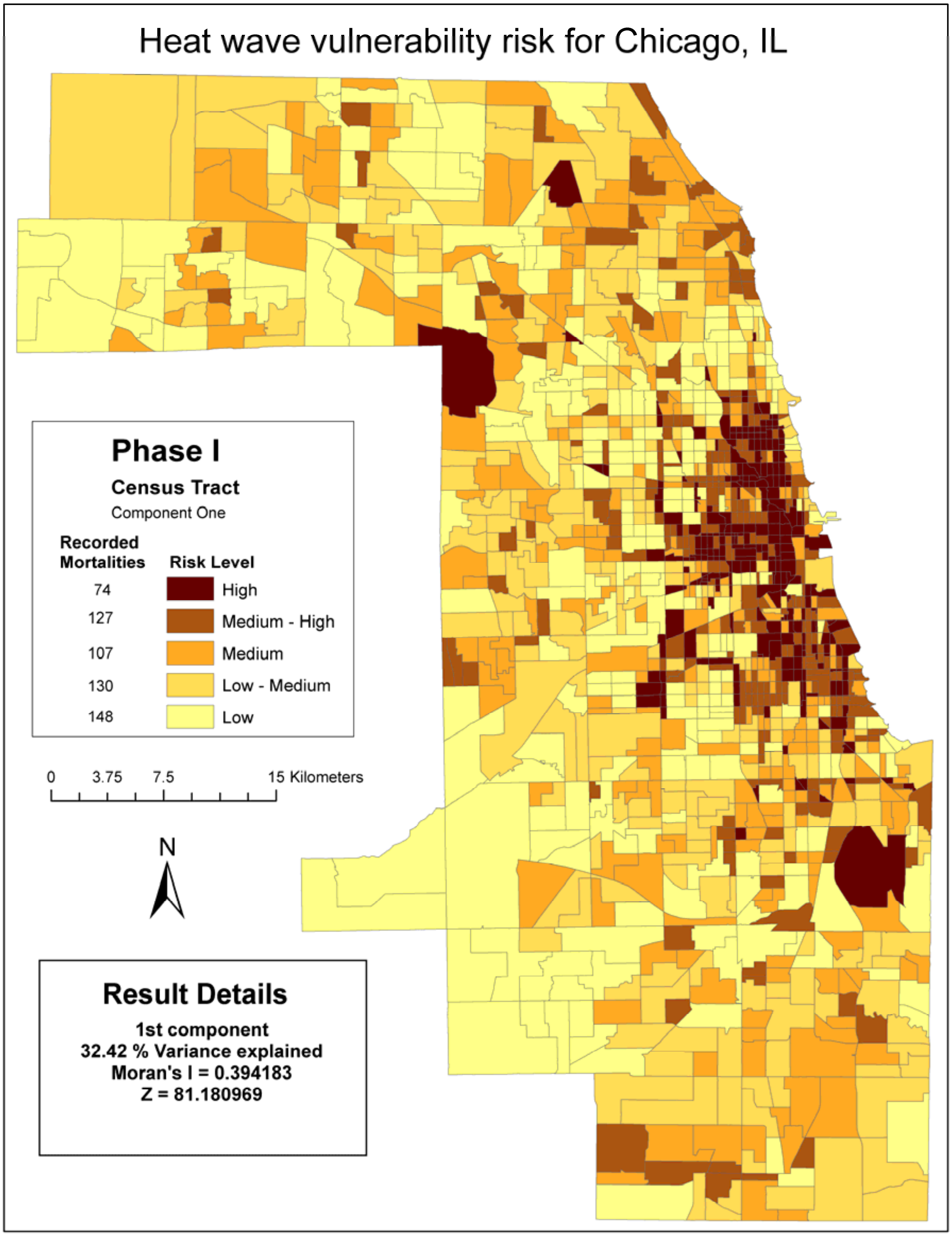

Heat wave vulnerability risk for Chicago, IL
Phase III
Block Group
Recorded Mortalities
Risk Level
139
High
110
Medium - High
107
Medium
97
Low - Medium
133
Low
0
3.75
7.5
15 Kilometers
N
Result Details
4 components
83.225 % Variance explained
Moran's I = 0.338233
Z = 164.312419


Heat wave vulnerability risk for Chicago, IL
Phase IV
Census Tract
Recorded Mortalities
Risk Level
154
High
96
Medium - High
104
Medium
116
Low - Medium
116
Low
0
3.75
7.5
15 Kilometers
N
Result Details
5 components
85.147 % Variance explained
Moran's I = 0.88566
Z = 182.219061

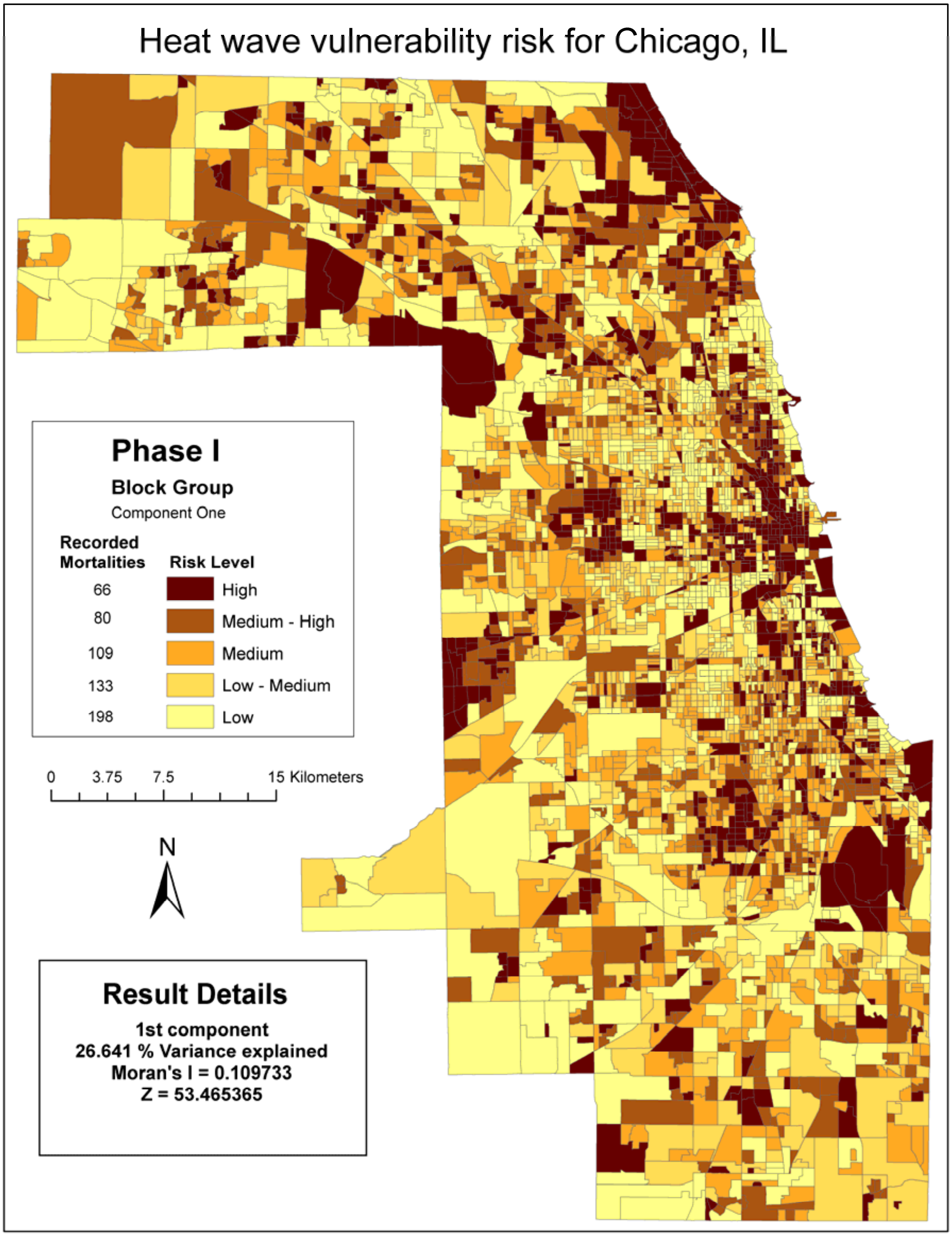

Heat wave vulnerability risk for Chicago, IL
Phase IV
Block Group
Recorded Mortalities
Risk Level
162
High
142
Medium - High
110
Medium
87
Low - Medium
85
Low
0
3.75
7.5
15 Kilometers
N
Result Details
5 components
84.356 % Variance explained
Moran's I = 0.370056
Z = 180.486898

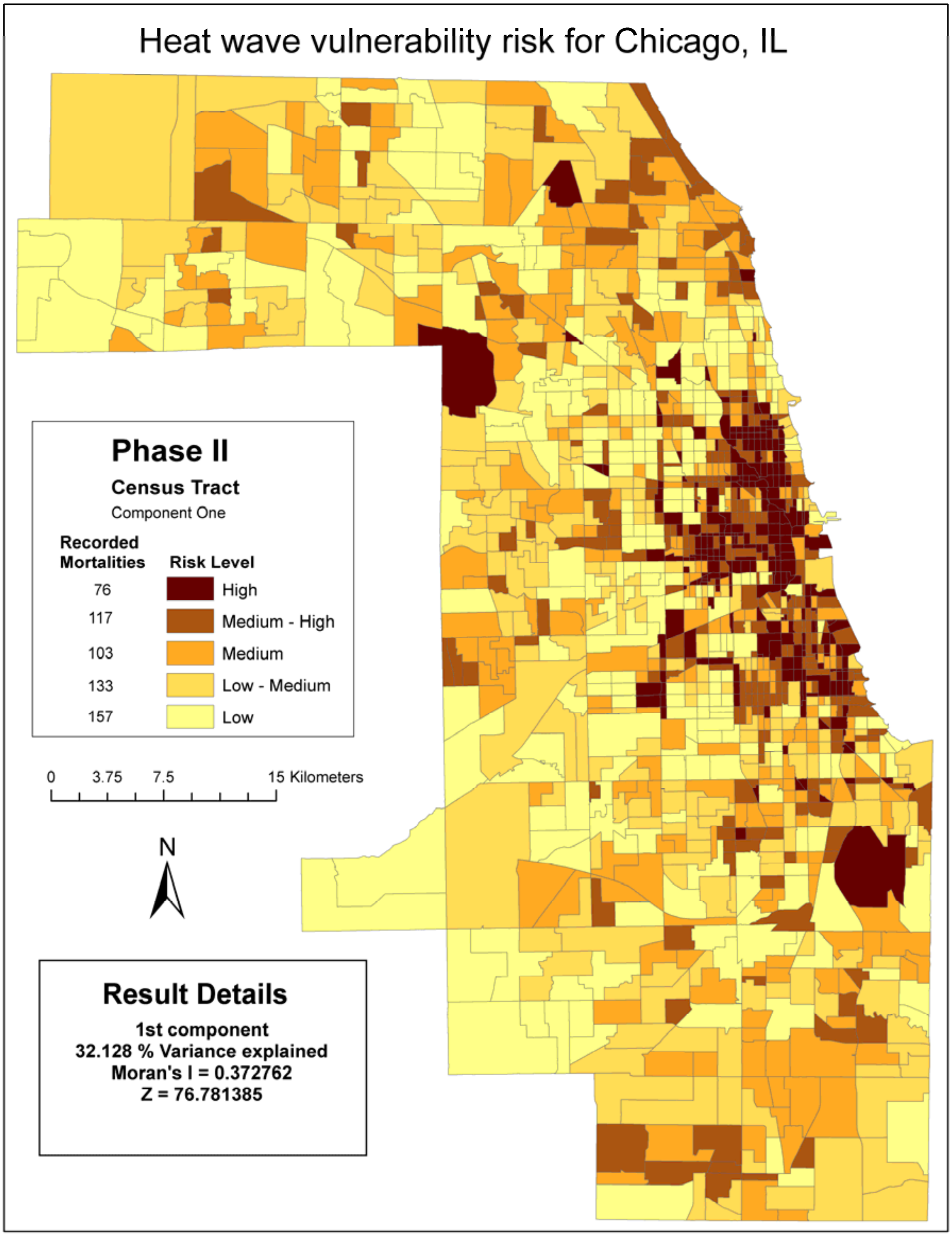
APPENDIX C

Vulnerability Maps of Component One

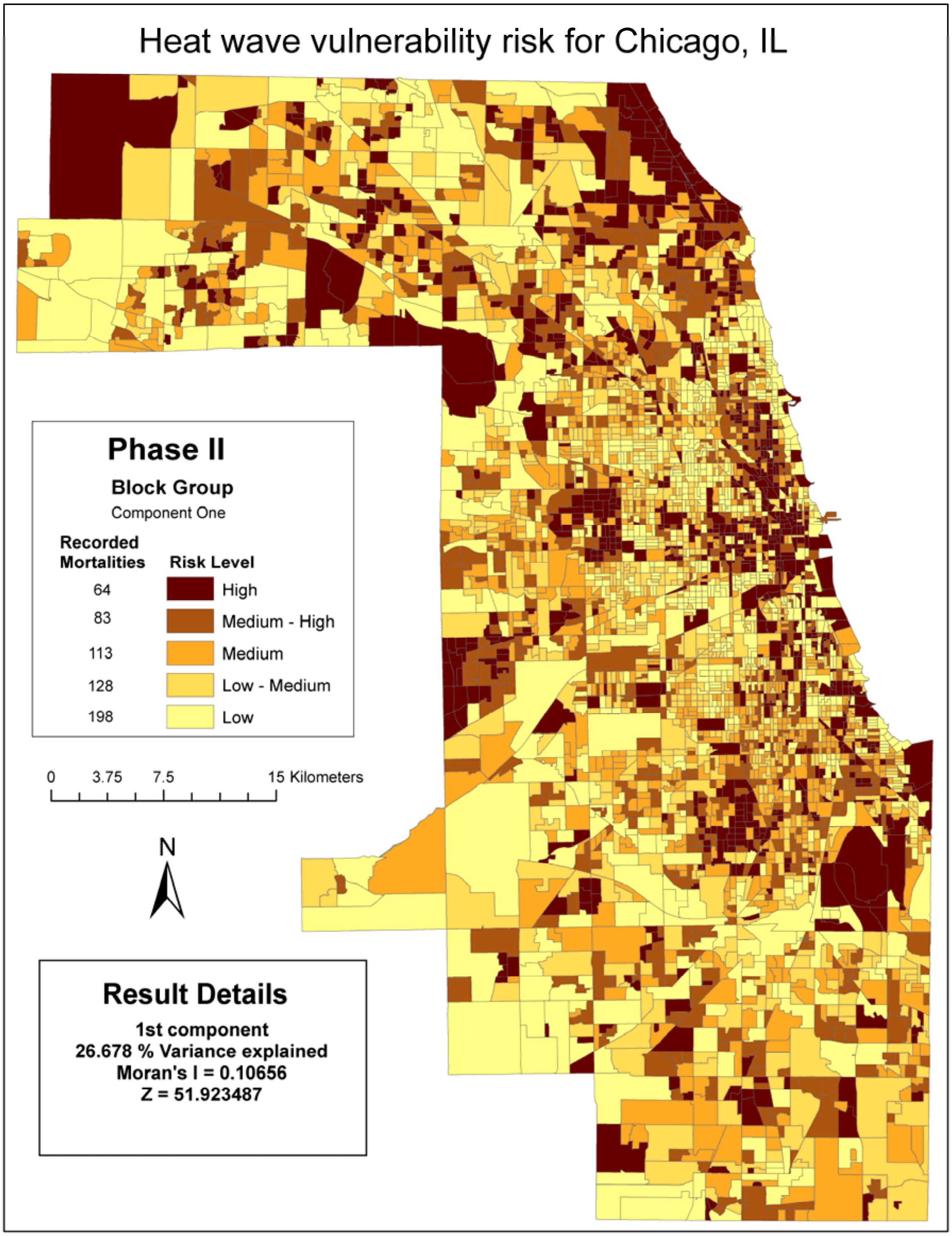


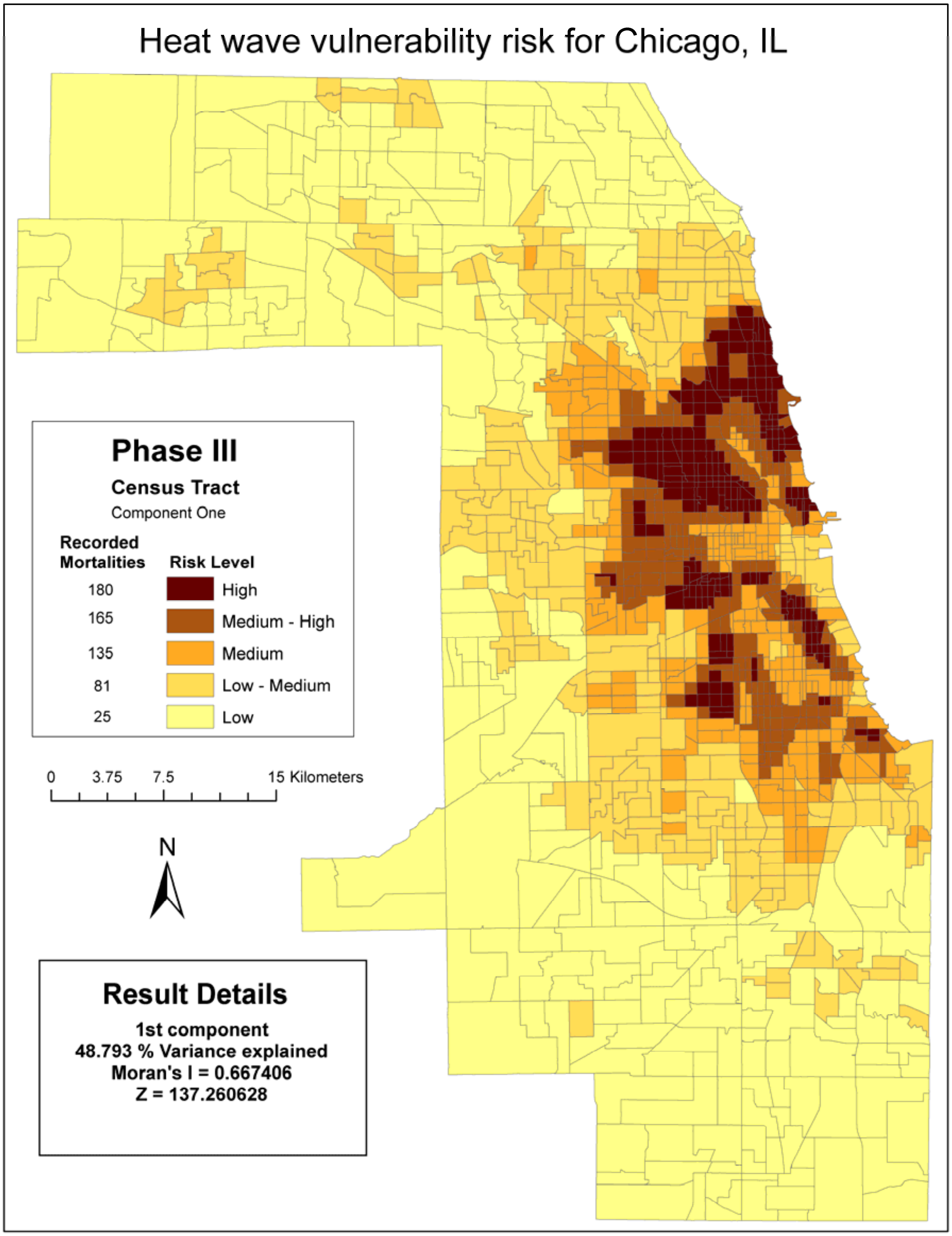
Heat wave vulnerability risk for Chicago, IL
Phase I
Census Tract
Component One
Recorded Mortalities
Risk Level
74
High
127
Medium - High
107
Medium
130
Low - Medium
148
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
32.42 % Variance explained
Moran's I = 0.394183
Z = 81.180969

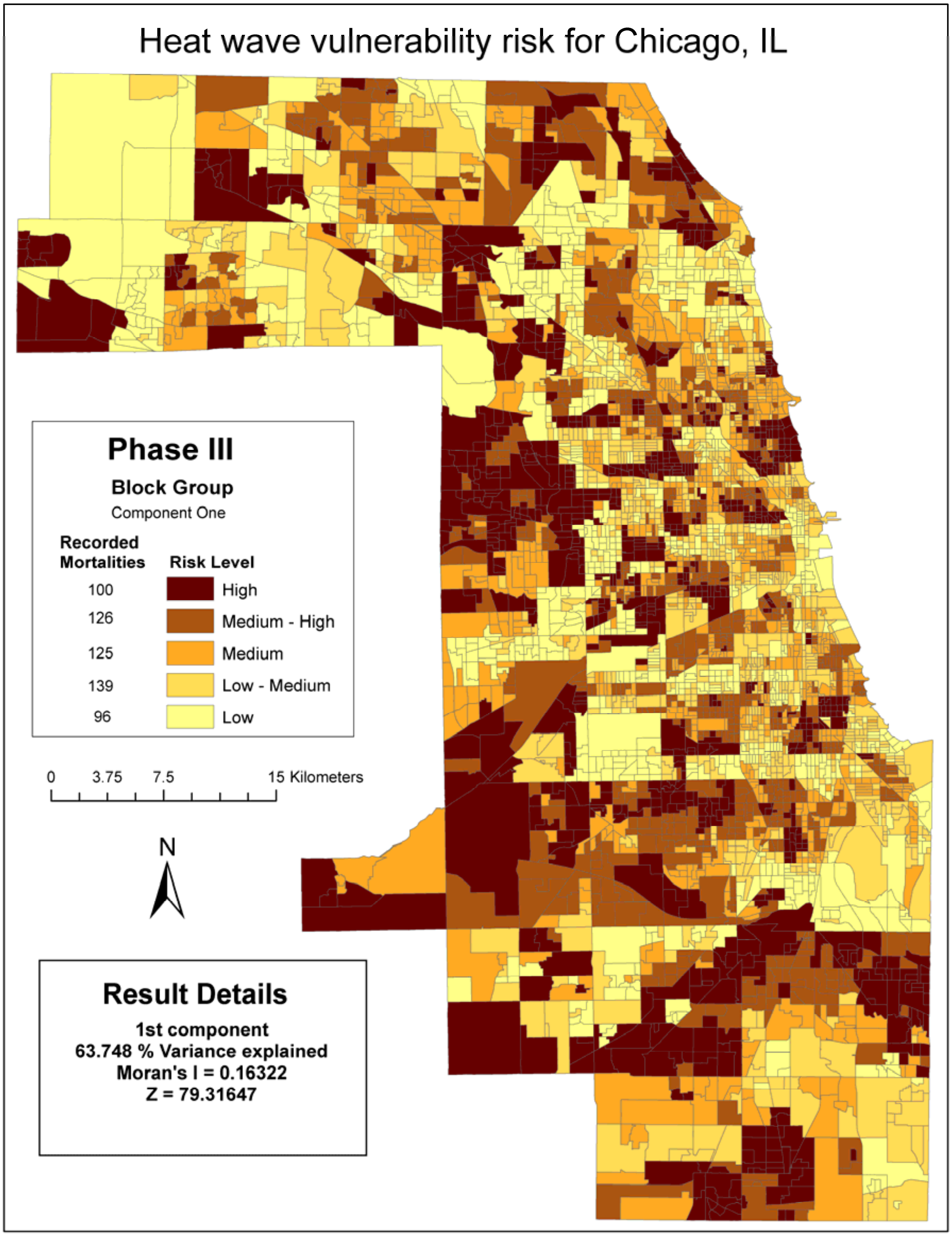

Heat wave vulnerability risk for Chicago, IL
Phase I
Block Group
Component One
Recorded Mortalities
Risk Level
66
High
80
Medium - High
109
Medium
133
Low - Medium
198
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
26.641 % Variance explained
Moran's I = 0.109733
Z = 53.465365

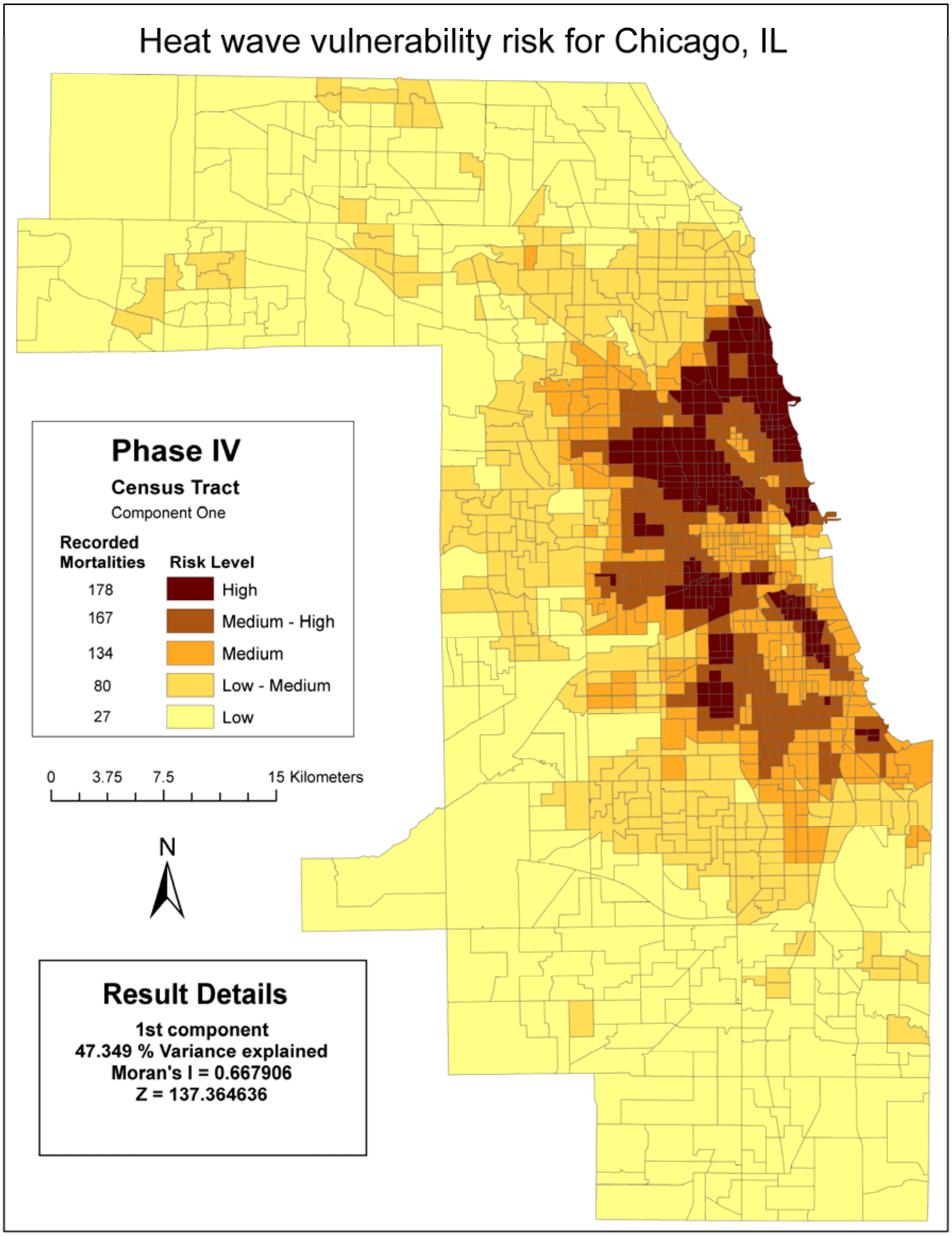


Heat wave vulnerability risk for Chicago, IL
Phase II
Census Tract
Component One
Recorded Mortalities
Risk Level
76
High
117
Medium - High
103
Medium
133
Low - Medium
157
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
32.128 % Variance explained
Moran's I = 0.372762
Z = 76.781385

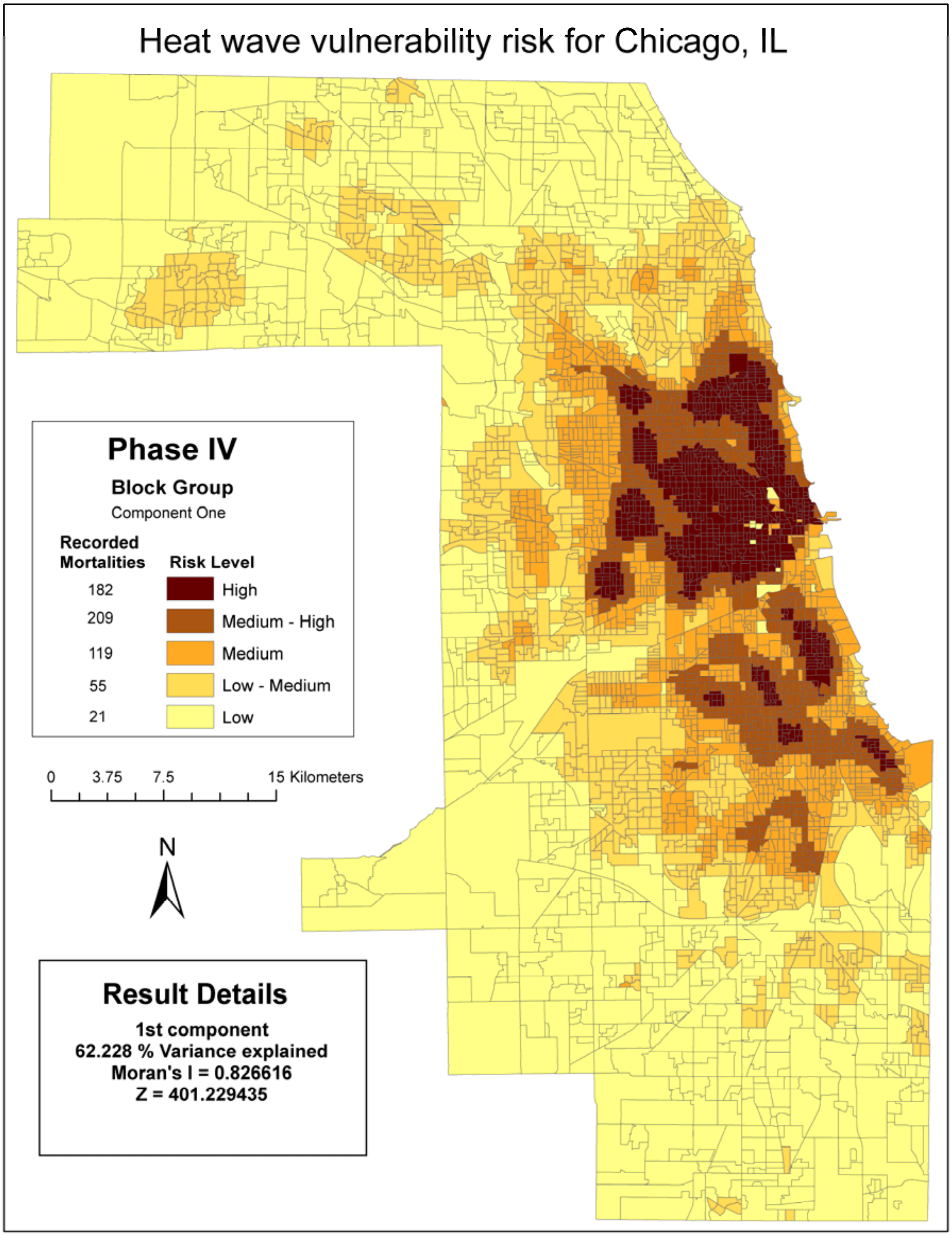

Heat wave vulnerability risk for Chicago, IL
Phase II
Block Group
Component One
Recorded Mortalities
Risk Level
64
High
83
Medium - High
113
Medium
128
Low - Medium
198
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
26.678 % Variance explained
Moran's I = 0.10656
Z = 51.923487


Heat wave vulnerability risk for Chicago, IL
Phase III
Census Tract
Component One
Recorded Mortalities
Risk Level
180
High
165
Medium - High
135
Medium
81
Low - Medium
25
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
48.793 % Variance explained
Moran's I = 0.667406
Z = 137.260628


Heat wave vulnerability risk for Chicago, IL
Phase III
Block Group
Component One
Recorded Mortalities
Risk Level
100
High
126
Medium - High
125
Medium
139
Low - Medium
96
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
63.748 % Variance explained
Moran's I = 0.16322
Z = 79.31647



Heat wave vulnerability risk for Chicago, IL
Phase IV
Census Tract
Component One
Recorded Mortalities
Risk Level
178
High
167
Medium - High
134
Medium
80
Low - Medium
27
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
47.349 % Variance explained
Moran's I = 0.667906
Z = 137.364636



Heat wave vulnerability risk for Chicago, IL
Phase IV
Block Group
Component One
Recorded Mortalities
Risk Level
182
High
209
Medium - High
119
Medium
55
Low - Medium
21
Low
0
3.75
7.5
15 Kilometers
N
Result Details
1st component
62.228 % Variance explained
Moran's I = 0.826616
Z = 401.229435

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CURRICULUM VITAE

Austin Curran Stanforth

Education
Indiana University – IUPUI, Indianapolis, IN
MS Geographic Information Science
June 2011

Butler University, Indianapolis, IN
BA Anthropology
Minor: Biology and Psychology
May 2007

Honors and Awards
Research Assistantship, Dept. of Geography and Center for Health Geographics, IUPUI, 2008 – 2011
Lesley A. Sharp Award for Excellence in Original Field Research, Butler University, 2007

Professional Experience
Department of Geography at IUPUI, Indianapolis, IN
Graduate Research Assistant *February 2008 - June 2011*

- Worked with aerial and satellite imagery to identify, digitize and map different land cover/land uses
- Conducted image interpretation and analysis
- Utilized ERDAS Imagine for multispectral image investigation
- Spatial Statistics and predictive modeling of environmental variables
- Created network files
- Analyzed Origin/Destination Cost Matrixes
- Conducted field research to support ongoing projects
- Created buffers, statistics and maps in ArcMap to show analysis of data and project status
- Used Garmin GPS tracking methods and converted waypoints into Shapefiles
- Design and create presentations and publications of original research

Center for Health Geographics, The Polis Center, IUPUI, Indianapolis, IN
Graduate Research Assistant *November 2008 - August 2009*

- Geocoded Areas of Interest for research projects
- Network relational analysis
- Integrated satellite imagery to produce land use/land cover maps
- Prepared and interpreted satellite imagery indexes for research
- Created intensity Raster images for analysis
- Database maintenance

Indy Parks and Recreation, Office of Land Stewardship, Indianapolis, IN
GIS Intern *July 2008 - December 2008*

- Designed and updated the Trimble GPS data collection system
- Built catalog of plants and parks used by the office within ArcCatalog
- Created Trimble data acquisition Quickforms to improve field data
- Collected GPS field data
- Implemented GPS data into maps and statistics to analyze project efficiency and outsource work contracts
- Created presentations in Power Point for management, pertaining to project audits and future project/fund planning
- Created GPS 'How to' documentation to assist new GPS users
- Mapped re-naturalization projects, exported maps to various programs for visualization
- Identified statistically superior trees to plant within flood zones for future planting projects

Office of the State Archaeologist, University of Iowa, Iowa City, IA
Field Technician *October 2007 - December 2007*

- Perform surface analysis for artifacts
- Excavate for Pre-Historical occupation materials
- Document and map artifacts

Conference Presentations

Stanforth, A. C. 2011. Identifying heat vulnerable populations across an urban environment, a case study of the 1995 Chicago, IL extreme heat event. Presented to the Centers for Disease Control and Prevention, May 2011, Atlanta, GA.

Stanforth, A. C. 2011. Identifying Variations of social-spatial vulnerability to heat-related mortalities during the 1995 extreme heat event in Chicago, IL. Paper presentation at the Association of American Geographers Annual Conference, April 2011, Seattle, WA.

Stanforth, A. C. 2011. Relating socio-spatial variables to heat induced mortalities during the 1995 extreme heat event in Chicago, IL. Poster presented at the Joseph Taylor Symposium, February 2011, Indianapolis, IN.

Stanforth, A. C., D. P. Johnson, V. Vulla, J. Webber III. 2010. Relating socio-spatial variables to heat induced mortalities in Chicago, IL during the 1995 extreme heat event. Poster presented at the ICEPHI Symposium, September 2010, Indianapolis, IN.

Stanforth, A. C. 2010. Relating socioeconomic variability to heat-related mortality during the 1995 extreme heat event in Chicago. Poster presented at the Association of American Geographers Annual Conference, April 2010, Washington, D.C.

Stanforth, A. C., J. Green. 2009. Remote archaeology- An experiment on the implications of remote sensing for archaeological research. Poster presented at the IUPUI Scholar Research Conference, May 2009, Indianapolis, IN.

Stanforth, A. C., S. L. Gidley, J. Green. 2008. Edge detection of historical African American homesteads in Indiana National Forest preserves. Poster presented at the IUPUI Scholar Research Conference, May 2008, Indianapolis, IN.

Publications

Johnson, D. P., A. C. Stanforth, V. Lulla. 2011. Remote sensing of heat-related risks: the trend towards coupling socioeconomic and remotely sensed data. *Geography Compass.* In print.

Johnson, D. P., A. C. Stanforth, and V. Lulla, 2011: Intra-urban variations in vulnerability associated with extreme heat events in relationship to a changing climate. C*limate Change*. In print.

Professional Memberships

Association of American Geographers
Golden Key International Honour Society